The Impact of Cultural Differences on Crowd Dynamics in Pedestrian and Evacuation Domains

Gal Kaminka

Bar Ilan University
Department of Computer Science and Brain Science Center
Computer Science Department
Ramat Gan, Israel 52900

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Accurate models of crowd dynamics are an important challenge in multi-agent systems and agent-based social simulation. Crowd models are able to predict the resulting macro level behavior from micro level interactions. However, many existing crowd models do not yet account for cultural factors in crowd behavior, and even more so, for crowds composed of members of different cultures. In this paper we examine the impact of cultural differences on the crowd dynamics in pedestrian and evacuation domains. In the pedestrian domain we relate to recorded pedestrian data in five different countries: Iraq, Israel, England, Canada and France and characterize these cultures based on cultural attributes at the individual level: personal spaces, speed, avoidance side and group formations. We use an agent-based simulation to investigate the impact on the resulting macro level behavior, such as pedestrian flow, number of collisions, etc. We also examine the impact of mixed-culture pedestrians on the resulting macro-level behavior. We quantitatively validate the simulation against data from movies of human crowds, in different countries. In the evacuation domain, we use an established simulation system to investigate cultural differences reported in the literature, and additionally explore the resulting macro level behavior.

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The impact of cultural differences on crowd dynamics in pedestrian and evacuation domains

Gal A. Kaminka
The MAVERICK Group
Computer Science Department
Bar Ilan University, Israel
{galk}@cs.biu.ac.il

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Abstract

Executive summary. This report continues EOARD-funded exploration of computational models of crowds and their behavior. In the first funded year (2008/9), we developed the social comparison model of group behavior and applied it to modeling pedestrian movement. In the second funded year (2010/11—a one year gap from the first funded year) we enhance this model with cultural capabilities, and model Iraqi, Canadian, Israeli, French, and English pedestrian crowds; we also apply our methodology to crowd evacuation simulations. Throughout this research, we have successfully evaluated the models again *real-world data, using recordings of various crowd behaviors and cultures*. Given this continued, we will propose continuation of this project, focusing on three activities (1) establishing a database of raw and annotated data, to serve crowd researchers world-wide; (2) expanding the queries supported by the model (e.g., being able to detect anomalous and suspicious behavior within a crowd).

Science summary. Accurate models of crowd dynamics are an important challenge in multi-agent systems and agent-based social simulation. Crowd models are able to predict the resulting macro level behavior from micro level interactions. However, many existing crowd models do not yet account for cultural factors in crowd behavior, and even more so, for crowds composed of members of different cultures. In this paper we examine the impact of cultural differences on the crowd dynamics in pedestrian and evacuation domains. In the pedestrian domain we relate to recorded pedestrian data in five different countries: Iraq, Israel, England, Canada and France and characterize these cultures based on cultural attributes at the individual level: personal spaces, speed, avoidance side and group formations. We use an agent-based simulation to investigate the impact on the resulting macro level behavior, such as pedestrian flow, number of collisions, etc. We also examine the impact of mixed-culture pedestrians on the resulting macro-level behavior. We quantitatively validate the simulation against data from movies of human crowds, in different countries. In the evacuation domain, we use an established simulation system to investigate cultural differences reported in the literature, and additionally explore the resulting macro level behavior.

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1 Introduction

Accurate models of crowd dynamics are an important challenge for agent-based so-cial simulations (e.g., for training, safety decision-support systems, pedestrian traffic management). Crowd researchers develop models that generate synthetic crowd behav-iors, that enable analysis, and that facilitate accurate predictions of macro-level crowd dynamics (resulting from micro-level interactions), when compared to actual human crowd behavior. This is particularly challenging when modeling physical crowds, such as pedestrians, evacuations, and demonstrations. These are our focus in this paper.

Unfortunately, existing models of physical crowds do not yet account for cultural factors. Social science literature on effects of culture in physical crowds is extensive when it comes to individual interactions (e.g., personal spaces and speed), but only rarely addresses macro-level phenomena (e.g., pedestrian flow). As a result, it is dif-fcult to validate models against data. This is particularly true of *mixed-culture physical crowds*, in which the rise of crowd dynamics out of individual interactions in inherently difficult to predict. And agent-based models have so far ignored cultural differences in physical crowd models (e.g., in pedestrians), treating all individuals as culturally ho-mogeneous, and adjusting cultural parameters ad-hoc.

As an example of such agent-based model, we refer to our own work. In re-cent years we have been successfully developing the social comparison model (SCT) of crowd behavior, inspired by Festinger's psychological theory of social compari-son [10]. In our previous work funded by EOARD, we quantitatively compared the performance of SCT crowd behavior model with that of popular crowd models in the literature, using real-world data. We demonstrated that SCT generates behavior more in-tune with human crowd behavior in pedestrian and evacuation domain[1].

However, despite its superior performance, the SCT model treats all agents as cog-nitively, physically and culturally identical. As a result, the model does not account for cultural differences that exist in different societies. For example, according to ex-isting SCT model pedestrians in Iraq and also in Canada would all walk in the same speed, and maintain the same distance between them. However, reports from social science indicate clear differences in the behavior of pedestrians in these different cul-tures: People in Iraq maintain different personal space and move in much larger groups than people in Canada.

Thus in this report, we extend the SCT model to account for the cultural differences in the spatial behavior preferences of pedestrians, and also to account for differences during evacuation scenarios. Some of the extensions to the model go beyond social comparison, and can therefore inform other agent-based simulations and of crowds.

Here, we take a step towards treating culture as a first-class object in models of physical crowds. We examine the impact of cultural differences on crowd dynamics in pedestrian and evacuation domains, using proven agent-based simulations of the two domains. We introduce cultural individual-level parameters into the simulations, and then examine the effects of these individual level parameters on the emergent crowd dy-namics. Moreover, we examine the effects of mixing individuals with different cultural

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[1]Work in the evacuation domain was initiated by the Window on Science program, and jointly carried out with the University of Southern California.

parameters in the same physical crowd.

In the pedestrian domain we relate the resulting culturally-aware simulation to pedestrian data which we recorded from videos of pedestrians in five different countries: Iraq, Israel, England, Canada, and France. We characterize these cultures along five individual-level parameters: personal spaces, speed, avoidance side (i.e., which side is preferred when avoiding an incoming pedestrian), and group formations. We use established crowd-level quantitative measures (e.g., flow, number of collisions, and mean speed) to identify crowd-level effects (e.g., the percentage of pedestrians that move in groups, and the gender- and age- mix of the groups). We show that the model can faithfully replicate the observed pedestrian behavior in these videos.

Cultural differences also have been found in evacuation domain. For example, Swedish participants evacuated more in groups than Australians that evacuated more individually. Based on literature we extract the cultural difference factors during the evacuation scenarios such as seriousness, notifying others and group behavior. It has been documented that some cultures take the event in different levels of seriousness and also in different level of fear. Moreover, it was found that in some cultures there is more tendency to notifying others about the event in comparison to other cultures. Finally, cultural differences also found to influence the manner in which people evacuate themselves, as there are cultures who tend to evacuate more in groups, while others prefer to evacuate individually more often. We model these factors in the evacuation scenario and show the impact of these factors on the resulting macro level behavior, such as evacuation time, average speed, panic level, etc.

2 Background and Motivation

Understanding and modeling cultural differences in crowd behavior is an important challenge for social and exact science researchers. Social psychology literature provides several views on the cultural differences in micro level interactions among groups of people, but they usually do not examine the influence of these differences on the resulting macro level behavior such as pedestrian flow. Exact science researchers can be inspired by social psychology literature for developing computational models for crowd behaviors, but their focus is to predict the resulting macro level behavior from micro level interactions. However, to the best of our knowledge, existing computational models for crowd behaviors do not yet account for cultural differences.

Social psychology. In social psychology there is an extensive research on the cultural differences in micro level interactions among groups of people. Cultural differences have been found in variety of human behaviors such as in different pedestrian dynamics, evacuation behavior and more. In pedestrian domain there are several cultural attributes that were examined across different countries such as the distance that pedestrian keep from one another, their walking speed etc. Cultural differences have been also found in evacuation behavior such as the way the people react to the event, the way people evacuate themselves etc. We provide here several examples for these cultural phenomena that were described in social psychology literature.

Hall [15, 12, 13, 14] examined the distances that pedestrian keep from one another

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across different cultures. He was one of the first researchers who defined the concept of *proxemics* which examines the spaces—invisible boundaries—that people maintain from each other in different contexts and cultures. According to Hall each person is surrounded by four invisible bubbles of space: *Intimate*, *Personal*, *Social* and *Public*. Personal distance refers to interactions among good friends or family members. Social distance refers to interactions among acquaintances and public distance is used for all other interactions such as public speaking. Changes in the distances depend, among other things, on relationships to the closest person and also on cultural background.

Beaulieu [3] examined cultural differences in personal space where she measured personal differences in four cultural groups. The research showed that Anglo Saxons used the largest zone of personal space, while Mediterraneans and Latinos used the shortest distance. Our analysis of human data partially supports her observations.

Levin and Norenzayan [20] examined the cultural differences in the the *pace of life* from 31 countries. According to their definition pace of life compound from three indicators: mean walking speed, the postal speed and the accuracy of public clocks. They showed that Japan has the fastest pace of live. They also showed people in England and France have faster walking speed than people in Jordan or Syria.

Berkowitz [4] provide an naturalistic study of urban pedestrians in six national groupings by analyzing their national social behaviors. His goal is to contribute to quantitative cross-cultural data on various pedestrian social behaviors. He examined 20 different locations in six different countries such as Italy, England, Iran, Turkey and more. This study shows that in Moslem countries, England and West Germany there is highest incidence of people in groups than in Italy and United States.

Chattaraj et. all., [8] examined whether there are cultural differences between Indians and Germans, in pedestrian streams in corridors. In an experiment they performed on pedestrians walking in straight lines, they found that the speed of Indian individuals is less dependant on density than the speed of German individuals. Moreover, they also found out that German groups keep higher personal space than Indian groups.

Patterson et. all., [23] examined the cultural differences in microinteractions of pedestrians in Japan and in United States as they walked past a confederate. They concentrate on effect of sex of confederate and his or her behavior when passing one another on the sidewalk such as glances, smiles, nods, greetings and more. The results show that pedestrians in Japan are less responsive in term of smile, node or verbalize a greeting than pedestrians in United States.

Cultural differences have been also examined in evacuation domain. Andrée and Eriksson [1] examined cultural differences between Swedish and Australian in evacuation scenarios. They conduct an experiments where they examined behavior and emotional patterns of 257 students from Sweden and Australia during the fire alarm and collect data by using questionnaires, video recordings and semi-structured interviews with the subjects. The results show that the Australians subject are more serious regarding the alarm than the Swedish and also they were more scared.

Bryan [7] also examined cultural differences in evacuation domain. He conduct an experiment which was involve 584 participants over 335 fire incidents and collect data by interviewing the subjects. He also compared the received results to the results of previous studies. He compared different parameters such as participants' awareness to the fire incident, the participants' first action during the incident and etc. The study

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showed among other results that different cultures tend to notify others about the existence of the event, to different extents. For example, in U.S there is a higher tendency of notifying others regarding the event than in England

Computational models.

Work on computer modeling of collective behavior has been carried out in other branches of science, in particular for modeling and simulation. Inspired by different science fields, researchers are developing computational models for simulation of collective behavior in order to be able to predict the resulting macro level behavior from micro level interactions. However, to the best of our knowledge, existing computational models for crowd behaviors do not yet account for cultural differences.

Henderson compared pedestrian movement to gaskinetic fluids. Based on experiments on real human crowds, he showed in [18] that crowd distribution is compatible with Maxwell-Boltzmann's distribution. Henderson [19] developed a pedestrian movement model based on Maxwell-Boltzmann theory. Since each person has mass and velocity, the crowd may be likened to liquid gas and under some assumption, the Maxwell-Boltzmann theory may be applied.

Based on Boltzmann-like equations, Helbing [16, 17] developed a general behavior model for simulation of crowd dynamics. The proposed model takes into account social forces caused by interaction between the individuals and external or spontaneous forces which are caused by the physical environment. It does not account for culture. Moussaïd et al. [22] examined the impact of groups motion on the pedestrian crowd dynamics. They showed that social interactions among group members create different group walking patterns and examine the impact of such patterns on the pedestrian flow. They results show that in low density group members tend to walk side by side, however, as the density increases the group members turning into a V-like pattern formation which reduces the flow because of its non-aerodynamic shape.

Adriana Brown et al. [6] examined how individual characteristics impact crowd evacuation. They expanded Helbing's physical model by adding individual parameters to each agent, such as dependence level and altruism level. According to the model, there will be a creation of groups which are combined from altruism and dependent agents. By changing these attributes, they examined crowd evacuation by measuring the flow of people passing the door per second, and population distribution in the flow.

Blue and Adler [5] proposed a different approach to model collective dynamics. They used Cellular Automata (CA) in order to simulate collective behaviors, in particular pedestrian movement. The focus is again on local interactions: Each simulated pedestrian is controlled by an automaton, which decides on its next action or behavior, based on its local neighborhoods. Blue and Adler showed that this simple rule results in the formation of lanes in movement, similarly to those formed in human pedestrian movement [29].

Toyama et al. [26] expanded the model by adding different pedestrian characteristics, such as speed, gender, repulsion level, etc. This allowed examining heterogeneous crowds, in pedestrian and evacuation behavior. Similarly, Durupinar et al. [9] explore heterogeneous crowd simulations in which individuals have varying personality traits, such as *extroversion* and *openness*. However, none of these models explore cultural differences.

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We use two agent-based simulations in our work. ESCAPES [27] is a an evacuation simulation, jointly developed by ourselves and the University of Southern California, incorporating four key features: (i) different agent types and ages; (ii) emotional interactions; (iii) informational interactions; (iv) behavioral interactions among agents. In ESCAPES, we investigated how each of these feature impact on the evacuation behavior. However, while this model accounts for variety of individual and social factors, it still not yet account for cultural differences among the agents.

The other agent-based simulation is of pedestrians. We rely on our previous model, SCT [11], which is a general model of group behavior which has been successfully applied to pedestrian and evacuation simulations. Both investigations explore a variety of individual and social factors, but do not yet account for cultural differences.

In this work, our goal is to develop a model of crowd behavior that can account for cultural differences in pedestrian and evacuation domains. By developing such a model we will be able to examine the impact of cultural differences on the resulting macro level crowd dynamics.

3 The Social Comparison Model of Crowd Behavior

In recent years we have been successfully developing the social comparison model (SCT) of crowd behavior, inspired by the social psychological theory of social comparison. We took Festinger's social comparison theory (SCT) [10] as inspiration for the social skills necessary for our agent in order to be able to exhibit crowd behavior. According to social comparison theory, when lacking objective means for appraisal of their opinions and capabilities, people compare their opinions and capabilities to those of others that are similar to them. They then attempt to correct any differences found. Section 3.1 shows how SCT can be turned into a concrete algorithm, to be used for generating crowd behavior.

However, the existing SCT model treats all agents as cognitively, physically and culturally identical. As a result, the model does not account for cultural differences that exist in different societies. For example, according to existing SCT model pedestrians in Iraq and also in England would all behave in the same manner. Section 3.2 presents the extension of the SCT model to account for the cultural differences in the spatial behavior preferences of crowds.

3.1 Existing Model of Social Comparison

According to our existing SCT (Social Comparison Theory) model, each observed agent A_i is taken to be a tuple of k state features $A \equiv \langle f_1^A, \ldots, f_k^A \rangle$. Each feature f_j^i of agent A_i ($1 \leq j \leq k$) corresponds to a dimension, such that agent A_i is represented by a point in a k-dimensional space, where the various dimensions correspond to state features (such as location in x, y coordinates, color, heading, etc.)

For each such agent, we calculate a similarity value $Sim(A_{me}, A_o)$, which measures the similarity between the observed agent A_o and the agent carrying out the comparison process A_{me}. The agent with the highest such value is selected. If its similarity is

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between given maximum and minimum values, then this triggers actions by the comparing agent to reduce the discrepancy. The process is described in Algorithm 1, which is executed by the comparing agent.

Algorithm 1 Argmax SCT $(O, A_{me}, S_{min}, S_{max})$

1: $S \leftarrow \emptyset$
2: **for all** $A_o \in O$ **do**
3:     **if** $S_{min} < Sim(A_{me}, A_o) < S_{max}$ **then**
4:         $S \rightarrow S \cup A_o$
5: $A_c \leftarrow \texttt{argmax}_{A_c \in S}(Sim(A_{me}, A_o)$
6: $D \leftarrow$ differences between me and agent A_c
7: $a \leftarrow$ SelectAction(D)
8: Apply action a with its Gain (Eq. 2) to minimize differences in D.

Each agent A_i executes the algorithm (Algorithm 1). In line 2 and 3, for each observed agent $A_o \in O$, we calculate a similarity value $Sim(A_{me}, A_o)$, which measures the similarity between the observed agent A_o and the agent carrying out the comparison process (A_{me}) (Eq. 1). We model each agent as an ordered set of features, where similarity can be calculated for each feature independently of the others. We measure similarity between agents independently along each dimension. The similarities in different dimensions are functions $s_{f_i}(f_i^{A_{me}}, f_i^{A_o}) : f_i \times f_i \mapsto [0, 1]$. The function s_{f_i} defines the similarity in feature f_i between the two agents A_{me} and A_o. A value of 0 indicates complete dissimilarity. A value of 1 indicates complete similarity. For instance, one commonly used feature denotes normalized Euclidean distance, inverted: A value of 0 means that the agents are as far apart as possible. A value of 1 means that they are positioned in the same location.

To determine the overall similarity between two agents, we use a weighted sum over the functions s_{f_i}. With each feature f_i, we associate a weight $w_i \geq 0$. The similarity between two agents is then given by Eq. 1 below.

$$Sim(A_{me}, A_o) \equiv \sum_{j=1}^{k} s_{f_j}(f_j^{A_{me}}, f_j^{A_i}) \cdot w_j \tag{1}$$

For each calculated similarity value, we check in line 3 if it is bounded by S_{min} and S_{max}, and in line 5 we pick the agent A_c that maximizes the similarity, but still falls within the bounds. S_{min} denotes values that are too dissimilar, and the associated agents are ignored. Festinger writes [10]: "When a discrepancy exists with respect to opinions or abilities there will be tendencies to cease comparing oneself with those in the group who are very different from oneself". Respectively, there is also an upper bound on similarity S_{max}, which prevents the agent from trying to minimize differences where they are not meaningful or helpful. For instance, without this upper bound, an agent that is stuck in a location may compare itself to others, and prefer those that are similarly stuck in place.

In line 6, we determine the list of features (f_i, w_i) which cause the differences between A_{me} and the selected agent A_c (list of features with $f_i < 1$). We order these

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features in an increasing order of weight w_i, such that the first feature to trigger corrective action is the one with the lowest weight. Thus, the correction order increases from lowest weight to the highest one. The reason for this ordering is intuitive, and we admittedly did not find evidence for it (or against it) in the literature.

Finally, in step 7 of the algorithm, the comparing agent A_{me} takes corrective action (a) on the selected feature. Note that we assume here that every feature has one associated corrective actions that minimize gaps in it, to a target agent, independently of other features. Festinger writes [10]: "The stronger the attraction to the group the stronger will be the pressure toward uniformity concerning abilities and opinions within that group". To model this, we use a gain function $Gain$ (Eq. 2), which translates into the amount of effort or power invested in the action. For instance, for movement, the gain function would translate into velocity; the greater the gain, the greater the velocity.

$$Gain(Sim(A_{me},A_c)) \equiv \frac{S_{max} - S_{min}}{S_{max} - Sim(A_{me},A_c)} \qquad (2)$$

3.2 Extending the Social Comparison Model

The way pedestrians maneuver within group formations tends to vary between different cultures. For example, it has been observed that in Arabic cultures there is more of a tendency for men to walk in front of women than in Europe, where men and women usually walk side by side. We propose to extend the SCT model to account for hierarchical social comparison.

According to social comparison theory the tendency of people to compare themselves to others differs between different individuals. Social comparison researchers have reported that while some people prefer to make downward comparisons others may prefer to make their comparisons upward [28]. The main reason for these differences is the individual variance in personal and social variables. This tendency affects the target selection process ,meaning to whom people prefer to compare themselves and therefore inevitably the different reactions that people may have following these comparisons.

We expand the SCT mechanism to account for hierarchical comparison, upward and downward comparison. Each agent holds personal and social variables such as social class, comparison tendency etc. We define several social classes that agents can belong to. An agent that performs the social comparison process, instead of selecting one agent for comparison, will select several agents, one agent from each social class. Then, according to its sociological factors it will choose the final agent to compare with. Therefore according to the social class the behavior parameters will be updated.

The process is described in the following algorithm, which is executed by the comparing agent.

Algorithm 2 differs from the earlier algorithm in several ways. First, rather than selecting an action a and executing it, it returns a recommendation for a, with a weight β, as already been reported in our previous work and it is beyond the scope of this paper. We provide here only a brief description. The output of this algorithm is a tuple $\langle a, \beta_a \rangle$, where a is a recommended action and β represents the agent's attraction to the

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Algorithm 2 Hierarchical *SCT* ($O, A_{me}, S_{min}, S_{max}, B, C$)

1: $A \leftarrow \langle \rangle$
2: **for** $i \leftarrow 1$ to $|C|$ do **do**
3:      $S \leftarrow \emptyset$
4:      **for all** $A_o \in C_i$ do **do**
5:          **if** $S_{min} < Sim(A_{me}, A_o, C_i) < S_{max}$ **then**
6:              $S \rightarrow S \cup A_o$
7:      $A_i \leftarrow$ ChooseAgent(A_{me}, S, C_i)
8: $(A_c, C_j) \leftarrow$ GetAgentForComparison(A, v)
9: $D \leftarrow$ CalculateDifferences(A_c, A_{me}, C_j)
10: $\beta \leftarrow$ CalculateBeta($A_c, O, S_{min}, S_{max}, C_j$)
11: $a \leftarrow$ SelectAction(D, C_j)
12: return $\langle a, \beta \rangle$.

observed agents (with whom it compared itself). This enables the social comparison process to be implemented as secondary parallel process within the cognitive architecture. Whereas normally, actions are proposed (and selected) by architecture based on their suitability for a current goal (e.g., through means-end analysis), in our agent actions were also proposed based on their suitability for SCT. In other words, at every cycle, an agent would consider actions that advance it towards its goal and, it would also consider social actions that seek to minimize perceived differences to other agents. Thus, the SCT-proposed actions compete with the task-oriented actions for control of the agent.

Second, in this algorithm an agent selects several potential agents for the comparison, one agent from each social class. C represents a vector of social classes that agents can belong to. A is a vector of agents of size $|C|$, where A_i corresponds to the chosen agent from each social class C_i. Between all observed agents and for each social class C_i, we calculate the similarity value, and if the similarity value is within bounds (S_{min}, S_{max}), the agent A_o is added to the set S. Between all the selected agents from each social class C_i, a representative agent A_i is selected. Then, the agent for the comparison is selected by GetAgentForComparison(A, v) which receives the vector of the representative agents for each social class A and the vector of sociological factors v based on it an agent selects the agent for the comparison. Thus, A_c represents the chosen agent for the comparison, and C_j represents the social class to which the selected agent belongs to.

D gets a list of features which corresponds on differences between me and the compared agent A_c and also based on social class that this agent belongs to C_j. In this way different actions may be recommended according to different social classes that the selected agent is belongs to such as walk behind or walk next to the selected agent. Then, an agent calculates β value, which represents agent's attractiveness to the selected group. The function CalculateBeta($A_c, S, S_{min}, S_{max}, C_j$) receives the compared agent (A_c), the selected group (S) and the similarity bounds (S_{min}, S_{max}), the social class that the selected agent belongs to C_j and returns the β value.

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4   Cultural Differences in Pedestrians Domain

In this section we define the attributes that impact on pedestrian dynamics among different cultures. First, we want to define the cultural attributes that impact pedestrian dynamics across different countries. Based on literature reviews and experts consultations we refer to the following cultural attributes: personal space, base walking speed, avoidance side, and group formations (in particular gender-heterogeneity, size, and shape, e.g., whether side-by-side, or one gender in front[22]):

- Personal space is an invisible boundary that people maintain from each other. According to Hall each person is surrounded by four invisible *"bubbles"* of space [15, 12, 3]: Intimate, Personal, Social and Public. Intimate distance refers to embracing, touching or whispering. Personal distance refers to interactions among good friends or family members. Social distance refers to interactions among acquaintances and public distance is used for all other interactions such as public speaking. Changes in the bubbles depend, among other things on relationships to the closest person and also on cultural background. It has been found by sociologists that people in different cultures maintain different distances.

- Pedestrian walking speed has also been found to be another cultural attribute [20]. In some cultures pedestrians walk much faster than in others. For example, people in England and France have faster walking paces than people in Jordan or Syria.

- We refer to avoidance side as the side of passing other pedestrians in situations of collision avoidance. In order to avoid collisions pedestrians choose whether to avoid the other person on the right or left side. It has been found that side preference is also a cultural decision [21]. For example, pedestrians in continental Europe tend to walk more on the right side of the sidewalk, whereas, in Japan or Korea, pedestrians are reported to walk more on the left side.

- In group formations we examine the portion of pedestrians that walk as individuals versus as groups, and also whom the groups consist of. For example, we differentiate between gender-homogeneous and heterogeneous groups. It has been reported that up to 70% of the people in a crowd move in groups such as families or friends versus individuals [22]. In this work we distinguish between individuals versus groups and also by size and gender group formation. For example, according to experts, people in Arabic countries walk in larger groups that people in Europe. Moreover, it has also been observed that in Arabic cultures there is a larger tendency for men to walk before women than in Europe, where men and women usually walk side by side.

To quantitatively characterize the examined cultures based on the presented cultural attributes, we analyze videos of human pedestrian dynamics where pedestrians from different countries walk on sidewalks. We quantitatively measure these in movies taken in five different cultures: Iraq, Israel, England, Canada and France. Then we use a pedestrian simulation to show the impact of these cultural attributes on the resulting

macro-level crowd dynamics. In the following section we provide a detailed description of the video analysis process and present our results.

4.1 Video Analysis of Human Pedestrian Dynamics

Overall, we collected over a hundred hours of pedestrian footage in different locations. In some, we only have a few minutes of video; in others, many hours:

- The movies from France were recorded in Paris from the top of the Eiffel tower. The movies were taken in the afternoon and portray two streets that lead to the Eiffel tower. In total we analyzed two movies of two different locations that are 1:40 and 2:47 minutes long.

- The movies from Iraq were recorded from a web camera overlooking the yard in front of the Hussein mosque in Karbala. In total, we recorded over 30 different, three hour long videos (over 90 hours) in this location. The videos were recorded during different parts of the day. About a third of the videos were irrelevant, showing static views, or showing that the web camera was off, etc. Of the remaining videos, we randomly chose six of the movies and analyzed the first three minutes of each. Thus, in total we utilized 18 minutes of pedestrian dynamics in Iraq.

- The movies from Israel were similarly recorded from a web camera overlooking The Western Wall in Jerusalem. We recorded over 30 videos during different parts of the day, again each three hours long. A third of these videos were found irrelevant for the same reasons as in Iraq and among the remaining ones we randomly selected four movies and analyzed the first three minutes from each. Thus, in total we utilized 12 minutes of pedestrian dynamics in Israel.

- The movies from Canada were video taped from one of the streets in downtown Vancouver in the morning and also in the afternoon. In total we analyzed four movies that are 0:15, 0:24, 1:18 and 3:36 minutes long.

- The movies from England were video taped in London in two different locations: Two movies from the London Eye (1:23 and 0:31 minutes long), and once from the Millennium Bridge (31 seconds long).

For the purposes of the analysis, we used a total of 45 minutes. To extract the group formations, speed, and avoidance side parameters from the videos, we asked four subjects to analyze the movies. Each movie was analyzed by two different subjects and we used the mean value for each measure in our results. For example, to extract the group formations, the subjects counted the number of individuals and the number of groups. For each individual the subjects were asked to specify whether it is a man or a women. For each group the subjects were asked to specify the size of the group; couples, three people or more and also the gender- and age- mix of each group; two women, two men, men and woman, woman with child, etc. To estimate speed, the subjects sampled 10 pedestrians in each movie, counting their steps within 15 seconds.

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To convert steps to an estimated velocity measurement, we can use the known average human step length for adults ($75cm$).

To determine the personal spaces between people in the movies, we used aerial photography and satellite image interpretation techniques which involve the estimation of size from images. To be able to measure the length, width and perimeter of specific object successfully, it is necessary to know the scale of the photo. To do this, we measure the size of a few well-known objects to give a comparison to the unknown object. In each movie we tried to estimate personal spaces with two techniques: Using "Google Earth" to determine object sizes, or estimate size based on the known size of familiar objects (such as cars or sports-field dimensions). If only one technique was feasible, then we used only one measure; otherwise, we took the mean value between the two measures.

For example, in one Iraq movies there is a truck that passes among the pedestrians (Figure 1). A standard truck size if 8ft (2.4384m). We measured the size of truck width on the screen (marked yellow) and found out it was 0.98cm. We then drew a line between the two people in the movie (marked red) and found out it was 0.15cm on the screen. We then deduced that the distance in reality is: $(0.98/0.15) \times 2.4384m = 37cm$.
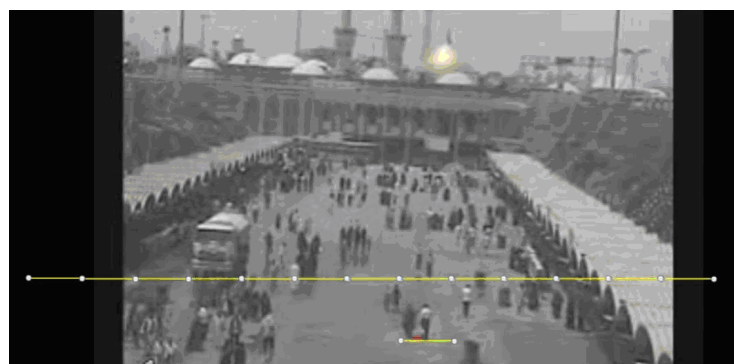
Figure 1: **Personal space estimation: Technique 1**

To verify, we use another method. Using "Google Earth" we found that the width of the area is 38m (including the white shades; Figure 2). Each segment in the 16-segment yellow line is therefore 2.375 meters. Again, simple math shows the distance is approximately 36 centimeters.

In each movie we tried to estimate personal spaces with these two techniques. If it was possible, we took the mean value between the two measures. If only one technique was possible, we used only one measure. For example, in Israel movies only the second technique was possible.

4.2   Results of Video Analysis

The results show that indeed the five countries differ from each other in the four cultural parameters. For lack of space, we present here only a subset of the estimated cultural

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Figure 2: **Personal space estimation: Technique 2**

parameters resulting from the video analysis. Our intent here is to demonstrate that these parameters actually vary between the cultures. Thus although some of the trends found are consistent with the literature, we do claim that they are representative of the culture in question.

4.2.1 Gender Group Formations

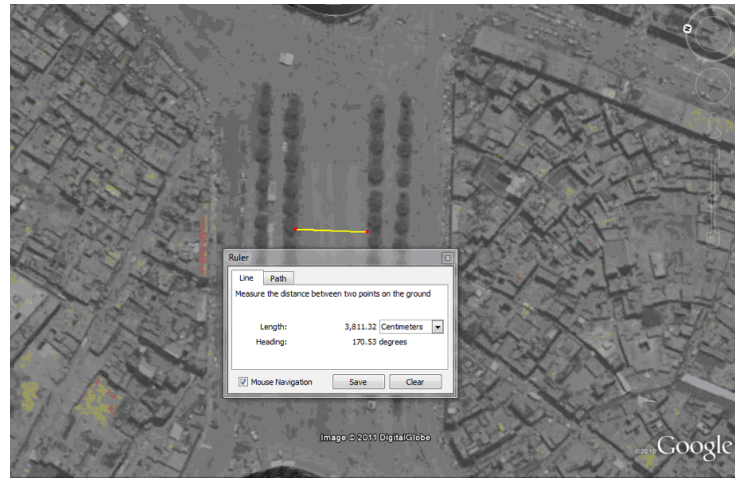We begin by examining groups and their makeup. Table 1 presents the results of gender group formations. The first column corresponds to the examined formations. Then we present the distribution of each such formation for each culture: Iraq, Canada, Israel and France. Each value is the mean value among two measures of two subjects. In the tables 2, 3, 4, 5 we present the statistics that we extract from this received data.

First we wanted to examine the portion of pedestrians that move as individuals versus as groups. Table 2 presents the results. The first column corresponds to the examine formation (individuals or groups). Then we presents the distribution of the pedestrians in each examined culture. The results show that in Vancouver, Canada people move more as individuals rather as groups. In every other country there is a higher tendency of pedestrians to move as groups.

We also wanted to examine among the pedestrians that move in groups whether there is a tendency to move in gender homogeneous groups or gender heterogeneous groups such as men and women are moving together. Table 3 presents the results. The results show that in Iraq, Canada, Israel and England, pedestrians more move in gender homogeneous groups. Indeed, in France we observed many couples such as man and woman are moving together.

Here, we wanted to examine the pedestrian cultural tendency regarding the group size. Among all the pedestrians that move in groups we provide a statistics regarding their distribution in groups with several sizes such as groups of 2, 3 and 4 and more.

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Formation	Iraq	Canada	Israel	England	France
man	20.9%	42.4%	33.3%	12.4%	9.21%
woman	6.88%	17.3%	14.6%	5.53%	4.61%
2 men	15.4%	14%	15.7%	24.9%	14.5%
2 women	12.3%	9.05%	11.8%	10.1%	11.8%
man next to woman	5.22%	4.94%	9.27%	24.9%	35.5%
man before woman	2.61%	0	0.36%	3.69%	5.26%
man & kid	0.71%	0	1.78%	3.69%	1.32
woman & kid	2.14%	0	1.43%	3.69%	0
3 men	8.9%	7.41%	6.42%	5.53%	0
3 women	7.47%	4.94%	4.28%	0	1.97%
man next to 2 women	4.27%	0	0.53%	2.76%	1.97%
man before 2 women	1.78%	0	0	1.38%	0
2 men & kid	0.71%	0	0	0	0
2 women & kid	1.42%	0	0	0	0
men, woman & kid	1.42%	0	0.18%	1.38%	5.92%
2 men & woman	0.71%	0	0	0	7.89%
2 men, woman & kid	0.47%	0	0	0	0
2 women & 2 kids	0.95%	0	0	0	0
3 men & kid	1.42%	0	0	0	0
man & 3 women	0	0	0	0	0
4 woman	4.27%	0	0	0	0

Table 1: **Results of gender group formation**

Formation	Iraq	Canada	Israel	England	France
individuals	28%	60%	48%	18%	14%
groups	72%	40%	52%	82%	86%

Table 2: **Group formation: individuals versus groups**

Table 4 presents the results. The results show that in Iraq there is a higher tendency to move in larger groups than in other examined countries.

According to experts men in Arabic countries have larger tendency to walk before his woman that in other countries, where men and women usually walk side by side.

Groups	Iraq	Canada	Israel	England	France
mixed groups	23%	12%	21%	42%	66%
homogeneous groups	77%	88%	79%	58%	34%

Table 3: **Group formation: gender homogeneous groups versus gender heterogeneous groups**

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Group size	Iraq	Canada	Israel	England	France
groups of size 2	64%	77%	84%	91%	85%
groups of size 3	30%	23%	16%	9%	15%
groups of size 4 and more	6%	0	0	0	0

Table 4: **Group formation: group size**

We wanted to examine the experts hypothesis whether such tendency is also observed in Iraq rather in other examined by us countries. Table 5 presents the results. The results show that in Iraq such tendency observed in 33% of couples which is much higher results than in other countries.

Formation	Iraq	Canada	Israel	England	France
man next to women	67%	100%	96%	87%	87%
man before women	33%	0	4%	13%	13%

Table 5: **Group formation: man and woman walking formation**

4.2.2   Pedestrian speed

We turn to examining individual speed, and its variance based on gender and grouping in the different cultures. Table 6 presents the results of pedestrians speed (measured in steps per 15 seconds; the conversion to distances introduces noise that is unnecessary at this point, and will take place only when we use the simulation for comparison). Here again, the first column corresponds to the examined formations. Then we present the mean speed among two samples of each examined formation and for each culture: Iraq, Canada, Israel and France. As in previous section, we then present the statistics that we extract from this received data.

Table 7 shows that men walk faster than women in all examined cultures. Between cultures, Iraqi pedestrians are the slowest (this agrees with previous research [20]). Moreover, in Iraq men as well as women are the slowest ones.

Next, we examine the effects of grouping on speed. Table 8 presents the results. Here we examine the mean speed of pedestrians that move as individuals versus mean speed of pedestrians that move in groups. The results show that in all cultures people as individuals move faster than people in groups.

Among all pedestrians that move in groups we wanted to examine whether there is a difference in mean speed between gender homogeneous groups versus gender heterogeneous groups. Moreover, we also wanted whether there is a difference in speed among groups of men versus groups of women. The results are summarized in Table 9. The results show in Iraq and England group of women are the slowest ones among the groups. However, in all cultures groups of men are the fastest ones among the groups.

Formation	Iraq	Canada	Israel	England	France
man	25.3	27.8	26.7	28.7	27.3
woman	22.1	27.6	24.9	23.5	26
2 men	23.2	27.8	24.5	26.2	26.3
2 women	20.6	31.2	22.6	24.1	26.3
man next to woman	23	28	22.5	25	24.8
man before woman					23
man & kid			31.5		
woman & kid					
3 men	23	30.5	25	28.7	
3 women	20	26.2	30		
man next to 2 women	23			20	
man before 2 women	22				
2 men & kid					
2 women & kid					
men, woman & kid					23.8
2 men & woman					24
2 men, woman & kid					
2 women & 2 kids					
3 men & kid					
4 woman	25.9				

Table 6: **Mean speed (in number of steps per 15 seconds)**

Formation	Iraq	Canada	Israel	England	France
men	25.3	27.8	26.7	28.7	27.3
women	22.1	27.6	24.9	23.5	26

Table 7: **Speed: men versus women**

4.2.3 avoidance side

In this section we present the results of the pedestrian avoidance side. Table 10 presents the results. The first column correspond to right or left avoidance side and then we presents the distribution of each examined cultures. The results show that in Iraq, Canada and England the pedestrians prefer the right side while in Israel and France pedestrians prefer the left side.

Formation	Iraq	Canada	Israel	England	France
individuals	25.1	28.6	25.7	26.5	26.6
groups	23	27.3	24.6	25	24.9

Table 8: **Speed: individuals versus groups**

Formation	Iraq	Canada	Israel	England	France
mixed groups	23.4	25.8	22.8	24.5	24
men homogeneous groups	24.1	28.8	26.3	26	26.8
women homogeneous groups	21.5	26.5	24.5	23.8	25.6

Table 9: **Speed: gender homogeneous groups versus gender heterogeneous groups**

avoidance side	Iraq	Canada	Israel	England	France
right	62%	63%	41%	77%	45%
left	38%	37%	59%	23%	55%

Table 10: **avoidance side: results**

4.2.4 Personal spaces

Finally, the video analysis shows that there are cultural differences in personal spaces. Table 11 shows the personal spaces within groups, as well as the mean personal space. It examines whether there is a differences in personal spaces kept by men and women in the same group. Here we distinguish between gender heterogeneous groups, men homogeneous groups and women homogeneous groups. The results show that in Iraq, Israel and France women keep less personal space than men. The biggest gap between group of men and group of women is observed in Iraq.

Group Type	Iraq	Canada	Israel	England	France
Mixed gender	26.5		46	50.3	35
Men only	43.8	65.8	66.5	49.5	57.5
Women only	18.3	70	50.3	52	40.5
Mean space	32.7	67.9	57.9	50.3	41.7

Table 11: **Personal spaces kept by men and women within the same group.**

5 Experiments in the Simulation of Pedestrians: Impact on Crowd-Level Measures

After establishing that the parameters chosen do indeed vary significantly between cultures, we turn to agent-based simulation to examine their effect on macro-level pedestrian dynamics. We used the popular OpenSteer [24] as the simulation platform. We simulated a sidewalk where agents can move in a circular fashion from east to west, or in the opposite direction. Each agent has limited vision distance (beyond this distance it cannot see). Agents are not allowed to move through other agents, in a case of possible collision the agents are tried to avoid it. The base pedestrian model was SCT [11], which was implemented fully and then extended to support the parameters noted above. The modifications to the original algorithm are described in Section 3.

To enable visibility of group formations, each agent is given a color: Individual men are colored in dark green, and individual women in gray. In families, the husband is colored blue, the wife is colored pink, and the children, who also have a smaller radius, have a yellow color. Agents in groups (non-family) are colored in light green if they are females, and in oranges in case they are males.

To account for cultural differences, each agent contains a set of cultural variables such as speed, personal spaces and avoidance side. Moreover, to account for group formations, each agent contains following variables: group id and social factors such as agent's comparison tendency and agent's social class which influence on the agent's social comparison process (the SCT process) to select the agent for the comparison, as described in section 3.2. To enable the at most accuracy in the simulation, we translate the received cultural variables data from the human movies analysis as described below.

- **Personal space**. We remind the reader that there are four spaces which people maintain: intimate, personal, social, public. Because of the limits of the simulation, we only model three of them: *personal*, *social* and *public*. Hall reported on two settings of distances for these three spaces: *close* and *far*. *Close* was defined as a personal distance of 46cm, social distance of 120cm, and a public distance of 370cm. *Far* is defined as a personal distance of 76cm, social distance of 210cm, and a public distance of 760cm. Because of high possibility for noise in our estimation of the personal spaces in human pedestrians movies and also since we measure only the distances among couples (which is personal rings), we use Hall's values of close and far. For each value that we received from the human movies data analysis we examine how close that value to one of Hall's rings. In the translation to the simulation, we normalized all the distances based on the shorted (46cm). Thus the three values for close ($\langle 46, 120, 370 \rangle$), translated to simulation distances of $\langle 1, 2.6, 8 \rangle$. Far ($\langle 76, 210, 760 \rangle$) translated to $\langle 1.65, 4.56, 16.5 \rangle$.

- **Speed**. In our simulation we define three levels of walk: slow walk, walk and faster walk. We analyzed the data extracted from the different cultures, and wanted to divide the speed samples into three levels of walk in our simulation. Among all the received samples of speed, we computed the 33th percentile and the 67th percentile, to get the two separators between these three groups (these turned to be the values 24.0 and 27.0, respectively.) This means that the three ranges of speed were: [20-24), [24-27), [27-31.5), as 20 and 31.5 are the minimum and maximum sample values, respectively.

  We then estimated the ratios between the speeds. Taking the mean of every range gives: 22, 25.5, 29.25 steps per 15 seconds. Various resources suggest 75cm as a solid estimation to a human average step [2] and convert the received number of steps per 15 seconds, to meters per second (giving us 1.1 m/s, 1.27 m/s and 1.46 m/s). Then we examine what speed in our simulation gives us the average speed 1.1 m/s. We found that by using the 2.27 speed in our simulation we get the average speed 1.1 m/s and based on the received ratios between the speed examined in human behavior we get the following speed level in our simulation: 2.27, 2.62 and 3.01.

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- **Avoidance side**. In situation of possible collision an agent choose whether to avoid the other agent on the right or left side. Each agent has a cultural preference of the avoidance side. This variable is initialized in the beginning of the simulation according to the analyzed human pedestrian dynamics movies and according to the culture that simulated agent is belongs to.

In all experiments described below, we examine the impact of individual cultural differences on the resulting macro-level pedestrian behavior, as measured by the following standard measures: (i) *the mean number of collisions* between two agents, averaged over all agents; (ii) the *observed mean speed* over all agents (this is different from the set individual speed, which each agent may or may not be able to achieve; and (iii) the pedestrian flow, i.e., the number of agents that cross a certain area divided by the length of the area and the time this process takes.

We ran extensive simulations with the above values, totaling over 100 hours of simulation. All results below are the averaged value over 30 trials.

5.1 Experiment 1: Impact of each of the cultural parameters on pedestrian dynamics

In this section we examine the impact of each cultural parameters on overall pedestrian dynamics. In all the experiments in this section, we fixed the sidewalk to be 110×20 and the number of agents to be 100. To account for group formations we divided our agents to be 30% individuals and 70% in groups as observed in some of the human movies, and also in [22]. We divide the agents to different group sizes and gender formations such as couples of women, 3 men groups, gender mixed couples, etc. as follows:

- Individuals: 30%

- Groups: 70%

    - 5/7 in 2-groups formations, which consists of:

        * Couples of men: 33%
        * Couples of women: 33%
        * Mixed couples: 33%

    - 1/7 in 3-groups formations, which consists of:

        * 3-men groups: 50%
        * 3-women groups: 50%

    - 1/7 in 4-groups formation which we defined to be husband, wife and 2 kids.

5.1.1 Speed

First we wanted to examine the influence of the mixed speed population on the produced pedestrian behavior. We initialized avoidance side of all the agents to right, the personal space of all the agents to close and group formation as defined in section 5.1.

We vary the percentage of agents with low (1.0) speed (versus fast walk which is 1.33): either 0% low speed, 20%, 50%, 80% or 100% and examine the impact of the mixed speed population on the pedestrian's flow, #collisions and #lane changes.

Figure 3 shows the influence of mix speed populations on the #collisions. The results show that the population that moves with the highest speed has the lowest number of collision. The average number of collisions where all the agents move with high speed is 0.27. The highest number of collisions is found in the mix population where 50% move with low speed and 50% with high speed (mean value: 0.5). Moreover, it is found out to be significantly different then speed homogeneous populations where all agents move with the high speed or low speed (two tailed t-test, $alpha < 0.01$ in both cases).
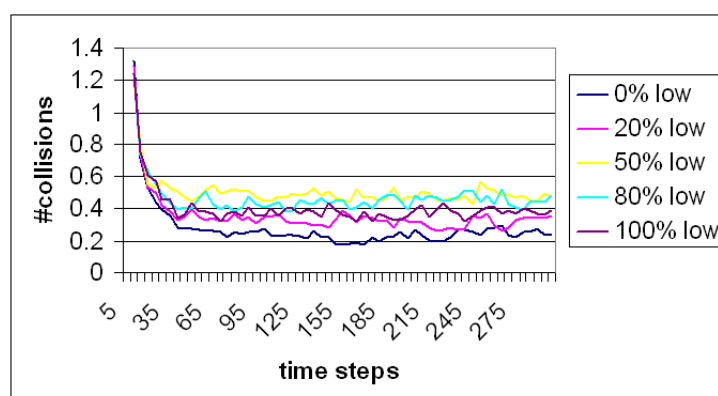
Figure 3: **The influence of mix speed population on #collisions**

Here, we wanted to examine whether agents' mix speed has influence on the #lane changes. Figure 4 represents the results. The results show that homogeneous speed (low or high) creates less number of lane changes. According to two-tailed t-test, there is no significant difference between high speed population and low speed population in number of lane changes, $alpha = 0.2$. Moreover, the mix speed populations creates the highest number of lane changes. The number of lane changes in population where 50% of the agents move with high speed and 50% move with low speed, has been found to be significantly different than the population where all agents move with low speed and than population where all agents move with high speed(two tailed, t-test $alpha < 0.01$ in both cases).

Figure 5 shows the influence of the mix speed population on the flow. The results are not surprising, the more agents that move with higher speed will cause to higher flow. As we can see in the results, the highest flow has been found in population where all agents move with the highest speed and the lowest flow is in population with lowest speed. However, what interesting is the ratio between changes in the population and the caused changes in the flow, for example if we increase our population from 0% low speed to 20% low speed the flow will decrease in 6%. Moreover, there is only 1% difference in flow between population where all agent move with lowest speed and
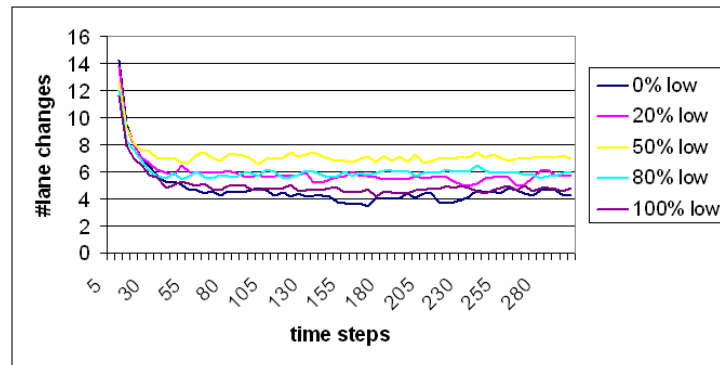
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Figure 4: **The influence of mix speed population on #lane changes**
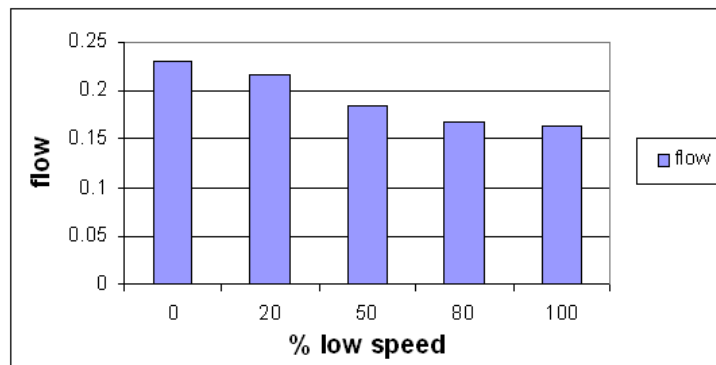
80% of agents that move with lowest speed.

Figure 5: **The influence of mix speed population on flow**

5.1.2 Personal space

In this experiment we wanted to examine whether the difference in personal spaces among the agents impact on the produced pedestrian behavior. We initialized avoidance side of all the agents to right, the speed of all the agents to 1 (which is slow walk) and group formation as defined in section 5.1. We vary the percentage of agents with close personal space (versus far personal space): either 0%, 20%, 50%, 80% or 100% and examine its impact on the pedestrian's flow, mean speed, #collisions and #lane changes.

First, we wanted to examine whether personal space impacts on the number of collisions between the agents. Figure 6 presents the results. The results show that there is a significant difference in number of collisions between the agent's with close personal space and far personal space (two tailed t-test, $alpha = 0.01$). The mean

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number of collisions in close personal space is 0.47 and in far personal space is 0.49 which is not a big difference between these values but it is found to be statistically significant. Surprisingly, the lowest number of collisions have been found in the mix group where 50% of agent move with close personal space and 50% with far. Moreover, there is a significant difference between far homogeneous group (all agents with far personal space) and heterogeneous group (50% of agents with close personal space and 50% with far) according to two tailed t-test, $alpha = 0.01$. However, no significant difference was found between close homogeneous group (all agents with close personal space) and heterogeneous group (50% of agents with close personal space and 50% with far) according to two tailed t-test, $alpha = 0.09$.
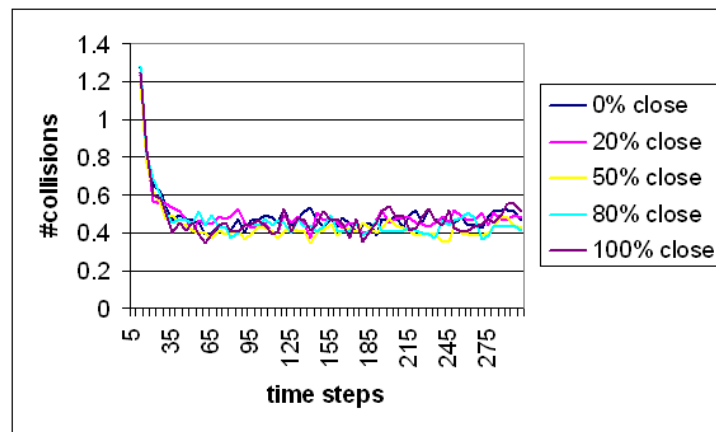
Figure 6: **The influence of personal space on #collisions**

Now we wanted to examine whether personal space impacts on the number of lane changes. The results are presented in graph 7. While it seems like there is almost no difference in the results, it has been found that there is a significant difference in number of lane changes between agent in close personal space and far personal space (two tailed t-test, $alpha < 0.01$). Agents in close personal space has lower number of lane changes. The results also shows that there is a significant difference between homogeneous groups (all agents in close personal space or in far personal space) and heterogeneous group (50% of agents with close personal space and 50% with far) according to two tailed t-test, $alpha = 0.01$ and $alpha = 0.03$.

Figure 8 shows the results of the influence of personal spaces among agents on their speed. The results show that agents with close personal space have higher mean speed than agents with far personal space, although both of the groups were initialized with the same speed. Moreover, there is a significant difference between agents with close personal space and far personal space, according to two tailed t-test, $alpha < 0.01$. The differences in mean speed also have been found between homogeneous groups (all agents in close personal space or in far personal space) and heterogeneous group (50% of agents with close personal space and 50% with far) according to two tailed t-test, $alpha < 0.01$ in both cases.
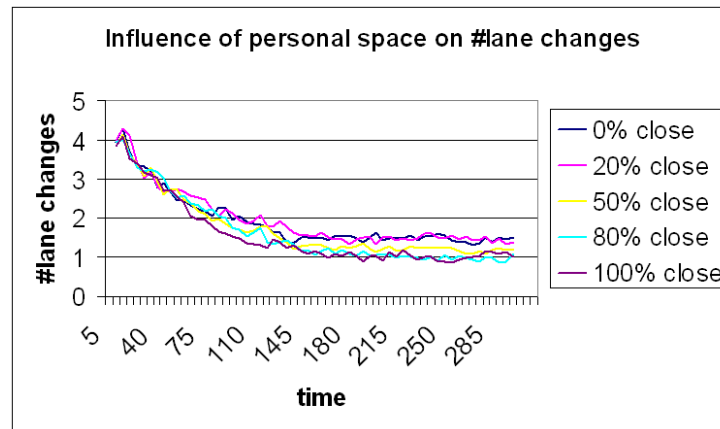
28

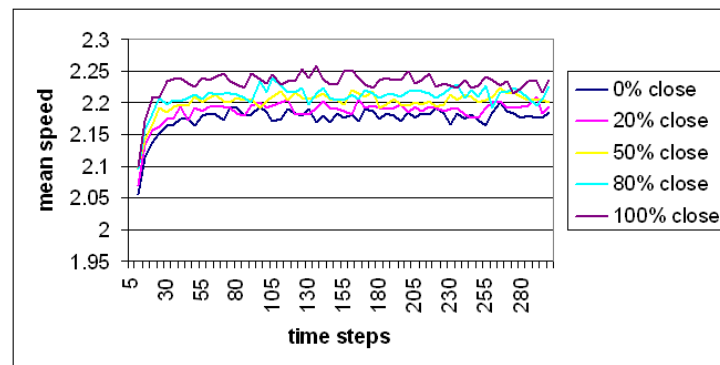Figure 7: **The influence of personal space on #lane changes**

Figure 8: **The influence of personal space on mean speed**

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We also wanted to examine the impact of personal spaces between the agents on the flow. Figure 9 presents the the results. The results show that agents with close personal space have higher flow than agents with far personal space. As has been shown in our previous results, the agents that move in far personal space have a higher number of collisions, a higher number of lane changes than agents in close personal space which influence on their mean speed and eventually on their flow.
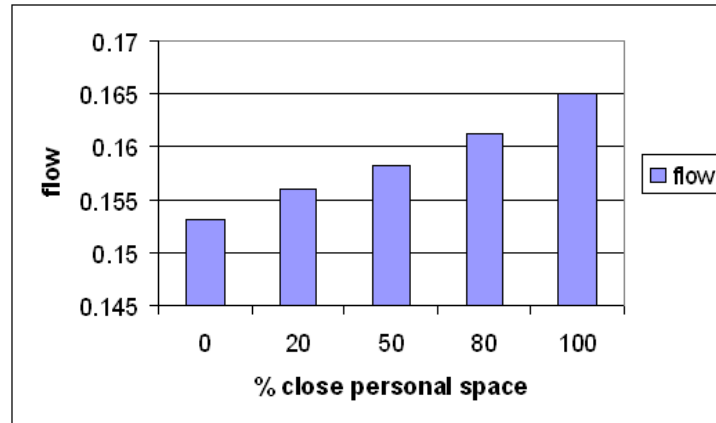
Figure 9: **The influence of personal space on flow**

5.1.3 Avoidance Side

Here we wanted to examine whether the pedestrian's avoidance side impacts on the pedestrian dynamics. In this experiment we initialized the speed of all the agents to slow walk, the group formation as defined in section 5.1 and the personal space of all the agents was defined close. We vary the percentage of agents with right-hand avoidance side (versus left-hand avoidance side): either 0%, 20%, 50%, 80% or 100% and examine the impact of these mix populations on the pedestrian's flow, mean speed #collisions and #lane changes.

First, we wanted to examine whether agent's avoidance side impacts on the number of collisions between the agents. Figure 10 presents the results. The results show that the lowest number of collisions is found in homogeneous groups where all agents are with right or left avoidance side. The highest number of collisions is found in heterogeneous group where 50% of agents with right avoidance side and 50% with left avoidance side. Moreover, there is a significant difference between homogeneous group (all agents with right avoidance side) and heterogeneous group (50% of agents with right avoidance side and 50% with left avoidance side) according to two tailed t-test, $alpha < 0.01$ in both cases.

Figure 11 represents the results of the influence of agents' avoidance side on the #lane changes. Similarly to the previous results, the lowest number of lane changes is found in homogeneous groups where all agents are with right or left avoidance side
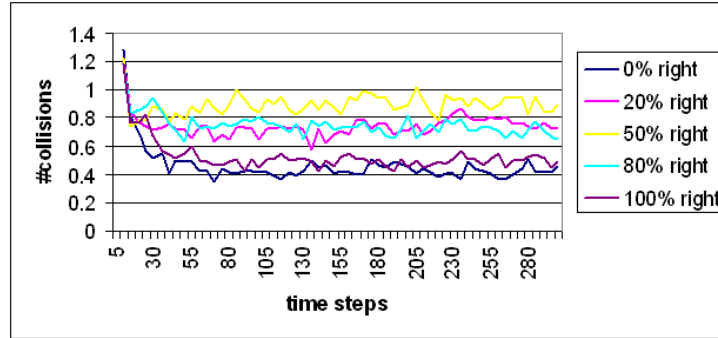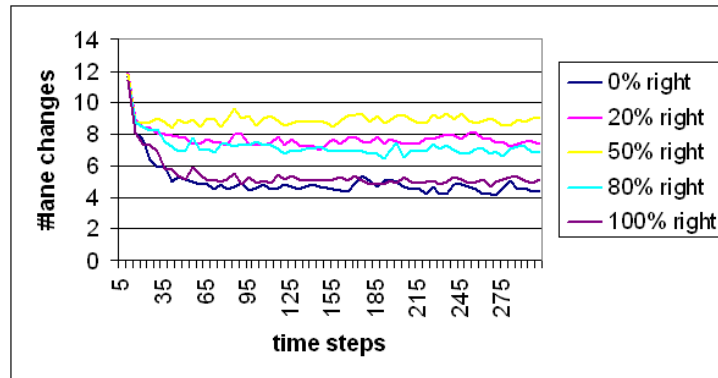
30

Figure 10: **avoidance side influence on #collisions**

and the highest number of lane changes is found in heterogeneous group where 50% of agents with right avoidance side and 50% with left avoidance side. Here again there is significant difference between homogeneous group (all agents with right avoidance side) and heterogeneous group (50% of agents with right avoidance side and 50% with left avoidance side) according to two tailed t-test, $alpha < 0.01$ in both cases.

Figure 11: **avoidance side influence on #lane changes**

We also wanted to examine the impact of the avoidance side on agents' mean speed. Figure 12 shows the results. The results show that homogeneous agents (all agents are with right or left avoidance side) have higher mean speed than heterogeneous agents (where 50% of agents with right avoidance side and 50% with left avoidance side). Moreover, there is a significant difference between these groups, according to two tailed t-test, $alpha < 0.01$ in both cases.

Now we wanted to examine the impact of agents' avoidance side on their flow. Figure 13 shows the results. The results clearly show that homogeneous agents (all agents are with right or left avoidance side) have higher flow than heterogeneous agents
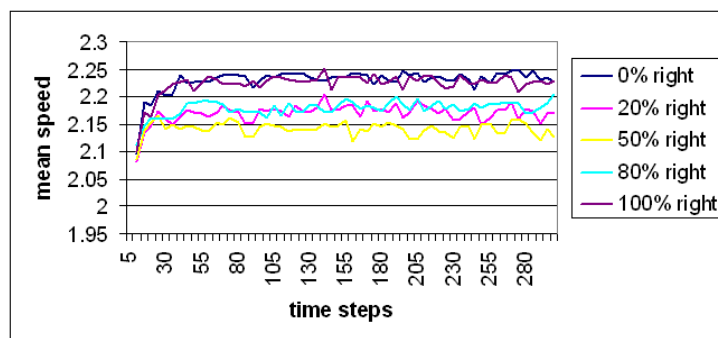
31

Figure 12: **avoidance side influence on mean speed**

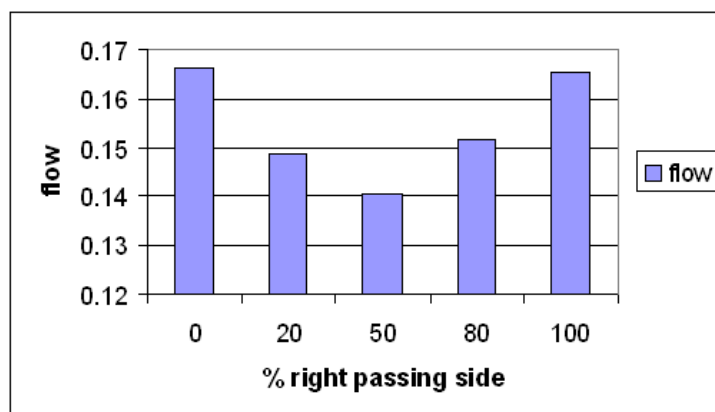(where 50% of agents with right avoidance side and 50% with left avoidance side).

Figure 13: **avoidance side influence on flow**

5.1.4   Group formations with fixed speed

In this experiment we wanted to examine whether the pedestrians movement in different groups has impact on the produced pedestrian behavior. We initialized avoidance side of all the agents to right, the speed of all the agents to slow walk and the personal space of all the agents was defined close. We vary the percentage of agents that move in groups (versus as individuals): either 0% in groups, 20%, 50%, 80% or 100% and examine their impact on the pedestrian's flow, mean speed and #collisions. Among all agents that walk in groups, the distribution to the different size and gender formations is the same as described above in 5.1.

Figure 14 shows the influence of groups on the #collisions. The results clearly show

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that higher number of groups in the population cause to higher number of collisions. Moreover, there is a significant difference in number of collisions between population where all agents are moving in groups and population where all agents are move as individuals, according to two tailed t-test, $alpha < 0.01$.
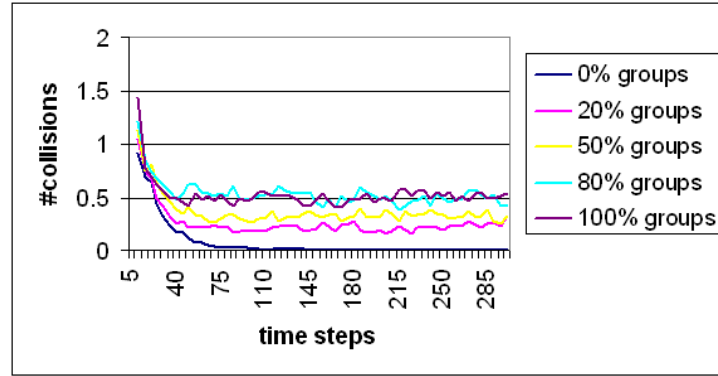

Figure 14: **Groups influence on #collisions**

We also wanted to examine the influence of groups on the number of lane changes. The results are described in Figure 15. The results clearly show the population where all agents move as individuals have the lowest number of lane changes. There is a significant difference in number of lane changes between population where all agents are moving in groups and population where all agents are move as individuals, according to two tailed t-test, $alpha < 0.01$. However, there is no significant difference between the homogeneous population where all agents are move in groups and heterogeneous population where 50% of agents move in groups and 50% move as individuals, according to two tailed t-test, $alpha = 0.1$.

Now we wanted to examine whether groups have influence on the pedestrian speed. Figure 16 presents the results. The results show that population where all agents move in groups have a higher speed which is a little bit surprising for us. However, the main reason for this is in order to keep the formations our agents occasionally accelerate which cause to higher speed.

Finally we wanted to examine the influence of group formations on the pedestrian flow. The results are presented in Figure 17. The results show that agents that move as individuals (0% groups) have a highest flow.

5.1.5 Group formations with vary speed

As in previous experiment we want to examine the impact of groups on the pedestrian dynamics. However, as we have show in section 4.2.2 genders and different groups formation, walk in different speed. In this experiment we initialize the speed of each formation (individual men, individual women, groups of men, groups of women and mixed groups) with the data taken from the human movies analysis (section 4.2.2) as the mean value for across all the five cultures we sampled.
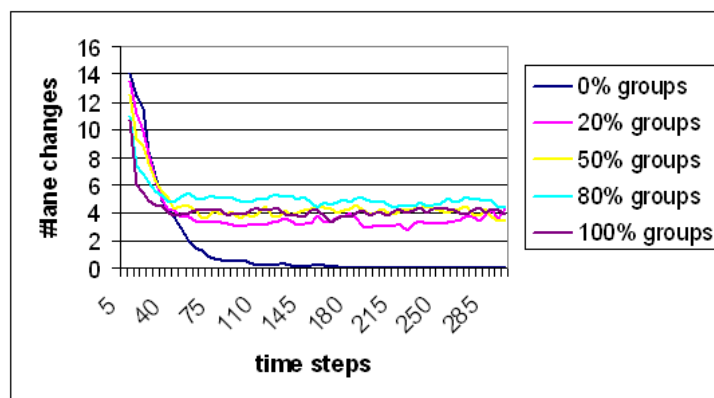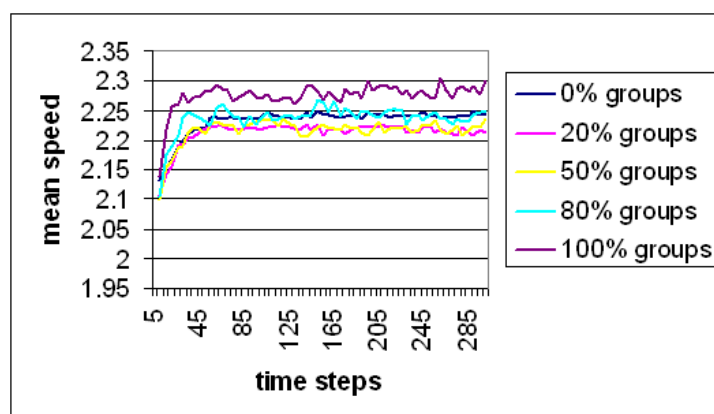
33

Figure 15: **Groups influence on #lane changes**
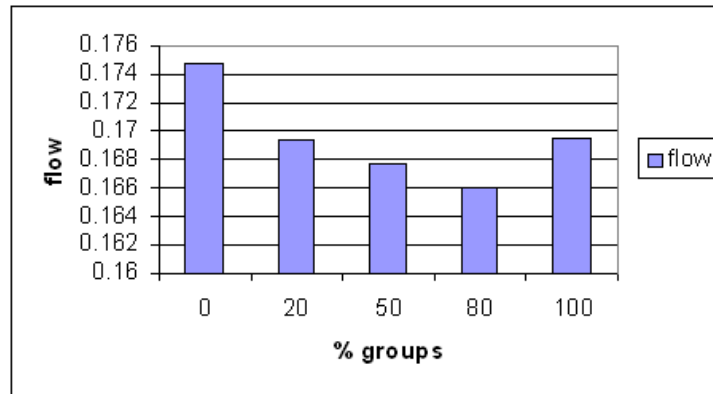

Figure 16: **Groups influence on mean speed**

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Figure 17: **Groups influence on flow**

Table 12 presents the mean values of different formations. The first column corresponds to the different formations and the second column corresponds to the mean speed across all the five cultures in the specific formation. The results show that individual men have the highest speed while group of women have the lowest speed.

Formation	Mean speed
Individual men	27.3
Individual women	25.3
Mixed group	23.9
Men homogeneous group	25.9
Women homogeneous group	23.7

Table 12: **Human video analysis: Mean speed of different formations**

Here again we initialized avoidance side of all the agents to right and the personal space of all the agents to close. However, the speed was initialized according to the formation that the agent belongs to. We vary the percentage of agents that move in groups (versus as individuals): either 0% in groups, 20%, 50%, 80% or 100% and examine their impact on the pedestrian's flow, mean speed and #collisions.

First we wanted to examine the impact of group formations on the pedestrians number of collisions. Figure 18 presents the results. The results show that individuals agents have the lowest number of collisions. The highest number of collisions was examined in mix population where 80% of agents move in groups and 20% as individuals (mean value: 0.63) which is higher than in homogeneous population where all agents move in groups (mean value: 0.57). Moreover, it also found out to be significantly higher, according to one tailed t-test, $alpha < 0.01$.

In this experiment we wanted to examine the impact of groups on the lane formation. Figure 19 represents results. The results show that higher number of groups
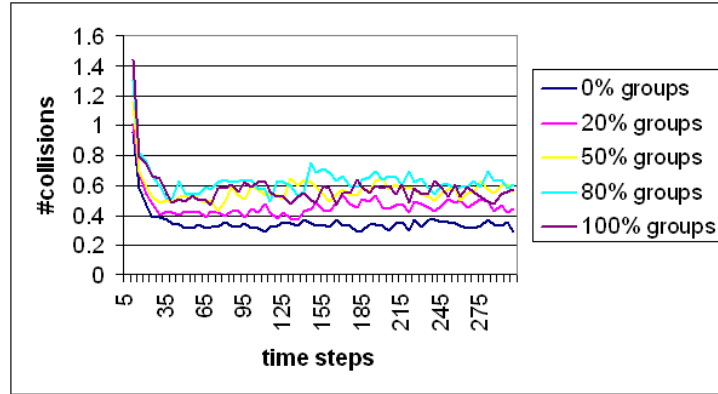
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Figure 18: **Groups influence on #collisions**

cause to higher number of lane changes. There is a significant difference in number of lane changes between population where all agents are moving in groups and population where all agents are move as individuals, according to two tailed t-test, $alpha < 0.01$. Moreover, there is also a significant difference between the homogeneous population where all agents are move in groups or as individuals and heterogeneous population where 50% of agents move in groups and 50% move as individuals, according to two tailed t-test, $alpha < 0.01$ (in both cases).
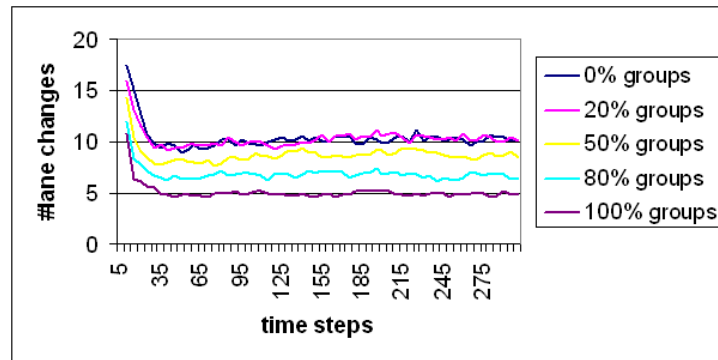

Figure 19: **Groups influence on #lane changes**

Now we wanted to examine the influence of groups on the pedestrian mean speed. Figure 20 shows the results. The results show that higher number of groups cause to lower mean speed. As in previous experiment there is a significant difference in mean speed between population where all agents are moving in groups and population where all agents are move as individuals, according to two tailed t-test, $alpha < 0.01$. Moreover, there is also a significant difference between the homogeneous population

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where all agents are move in groups or as individuals and heterogeneous population where 50% of agents move in groups and 50% move as individuals, according to two tailed t-test, $alpha < 0.01$ (in both cases).
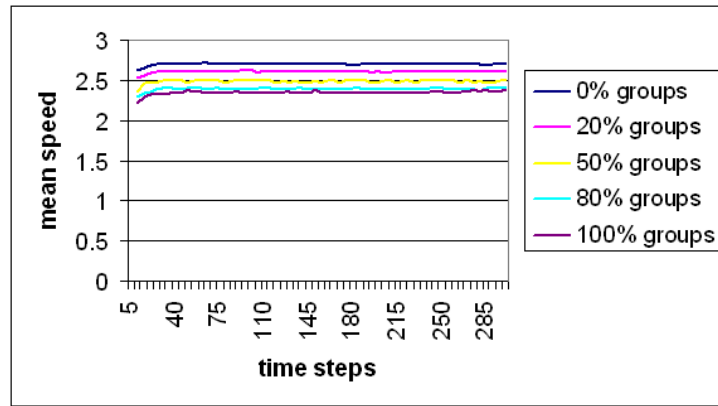

Figure 20: **Groups influence on mean speed**

Finally we wanted to examine the influence of group formations on the pedestrian flow. Figure 21 presents the results. The results show that agents that move as individuals (0% groups) have a highest flow. Moreover, higher number of groups cause to slower flow.
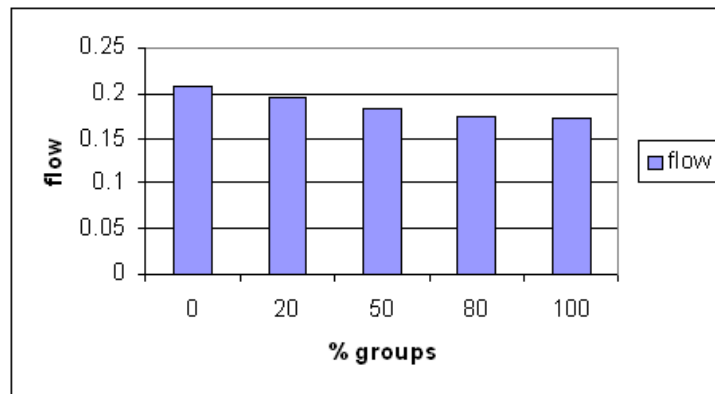

Figure 21: **Groups influence on flow**

5.2   Experiment 2: Differences between cultures

In this section we want to examine whether different cultures such as Iraq, Israel, England, Canada and France has a different impact on pedestrian dynamics. For each ex-

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amine culture we initialize each of the cultural parameters (frequencies of formations, speed, personal space and avoidance side) with the values extracted from real videos of this culture as presented in section 4.2.

First we wanted to examine whether there is a difference between cultures in pedestrians' number of collisions. The results are presented in graph 22. The results show that France has a highest number of collisions between the pedestrians. We believe that main reason for this is that in France there is more heterogeneous avoidance side than in other countries (45% prefer right avoidance side and 55% prefer left avoidance side). The lowest number of collisions has been found in Iraq.
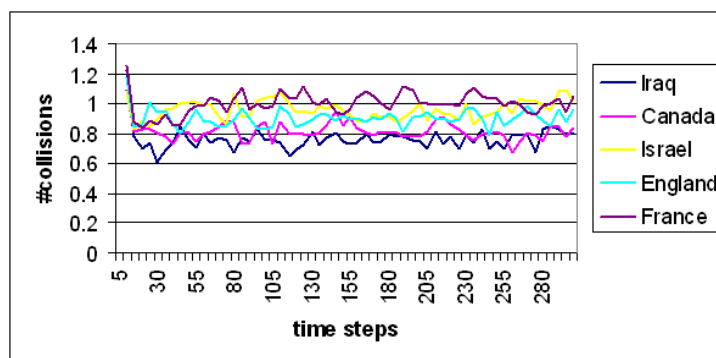

Figure 22: **Difference between cultures on #collisions**

In this experiment we wanted to examine whether there is a difference between cultures in pedestrians' number of lane changes. The results are presented in graph 23. The results show that the lower number of lane changes are in Iraq while in Canada there is a highest number of lane changes. The pedestrian in Canada keep the greatest personal space between one another which we believe is the main reason for this result as shown in section 5.1.2.

Now we wanted to examine whether there is a difference between cultures in pedestrians' speed. Figure 24 presents the results. The results show that pedestrian in Canada have a highest mean speed. The lowest mean speed has been found in Iraq. The results are not surprising for us. Based on the human video analysis in section 4.2 pedestrian in Canada move more as individuals and also have a higher speed than in other cultures, while pedestrian in Iraq are walk more as groups and have a much slower speed than in other cultures.

Finally we wanted to examine whether there is a difference between cultures in pedestrians' flow. The results are presented in graph 25. The results show that the highest flow has been found in Canada while Iraq, Israel and France have the lowest flow.
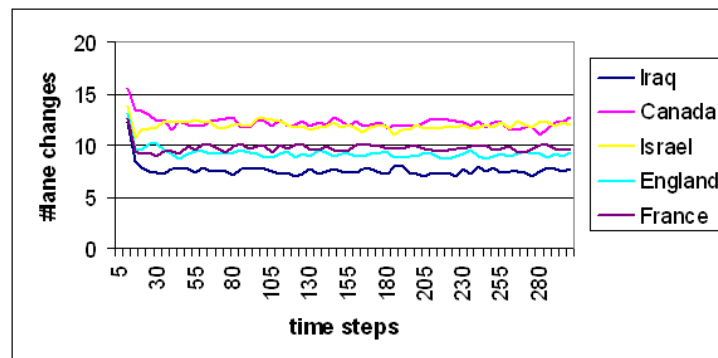
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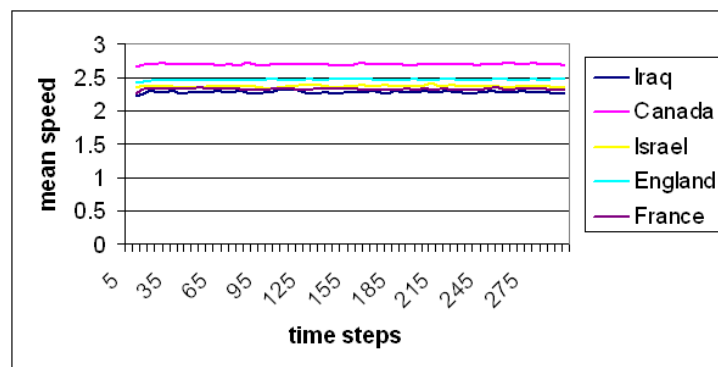Figure 23: **Difference between cultures on #lane changes**

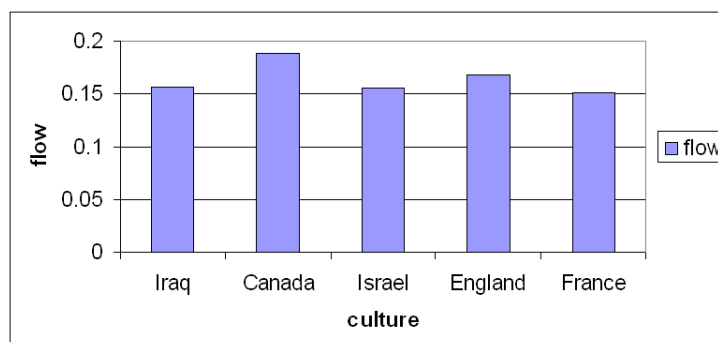Figure 24: **Difference between cultures on mean speed**

Figure 25: **Difference between cultures on pedestrians' flow**

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5.3 Experiment 3: Mixed Cultures

Finally, we want to examine whether there is an impact on the pedestrian dynamics when we mix cultures on the same sidewalk. For example: if we mix the population such as part of it is from Iraq and another part is from Canada, how this will influence on the pedestrian dynamics.

As it is infeasible to experiment with all the variations of cultures, we give the example of mixing between two cultures: Iraq and Canada. In this section we we define x% of the population to be from Iraq, and (100-x)% to be from Canada, and we vary with values of x: 20,50,80. As in previous section initialized each of the cultural parameters (frequencies of formations, speed, personal space and avoidance side) with the values extracted from real videos of this culture as presented in section 4.2.

First we wanted to examine the impact of such mix population on the number of collisions. The results are presented in graph 26. The results show that the higher the percent of Canadian in the population the higher the number of collisions. The lowest number of collisions has been found in population where 20% from Canada and 80% from Iraq. Moreover, there is a significant difference between population where 20% from Canada and 80% from Iraq, and population where 80% from Canada and only 20% from Iraq, according to two tailed t-test, $alpha < 0.01$.
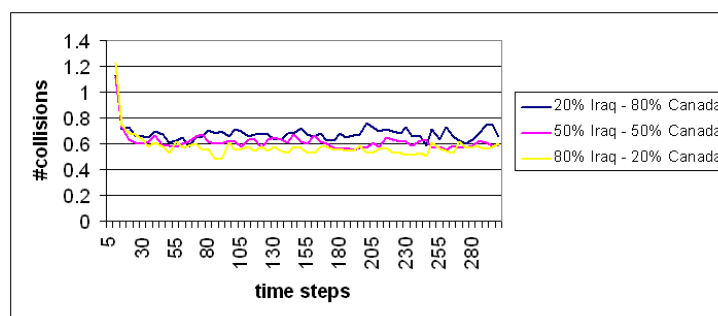

Figure 26: **Impact of mix population of Iraq and Canada on #collisions**

In this experiment we wanted to examine the impact of mix population (Canada and Iraq) on the number of lane changes. The results are presented in graph 27. As in previous experiment, the results show that the higher the percent of Canadian in the population the higher number of lane changes. Here again, the lowest number of collisions has been found in population where 20% from Canada and 80% from Iraq. Moreover, there is a significant difference in number of lane changes between population where 20% from Canada and 80% from Iraq, and population where 80% from Canada and only 20% from Iraq, according to two tailed t-test, $alpha < 0.01$.

Now we wanted to examine the impact of mix cultures on pedestrians' speed. Figure 28 presents the results. The results show that pedestrian the more Canadian in the population the higher the mean population speed. The lowest mean speed has been found in population where 80% from Iraq and 20% from Canada. As in previous experiments, there is a significant difference in mean speed between population where
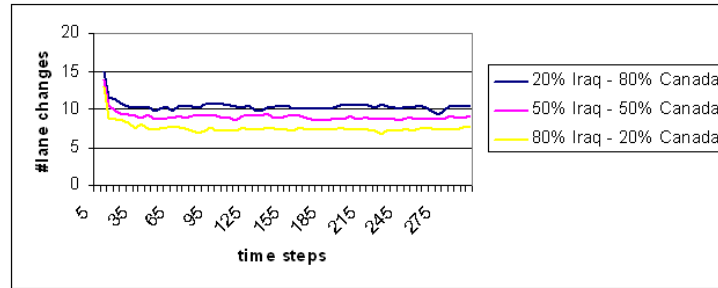
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Figure 27: **Impact of mix population of Iraq and Canada on #lane changes**

20% from Canada and 80% from Iraq, and population where 80% from Canada and only 20% from Iraq, according to two tailed t-test, $alpha < 0.01$.
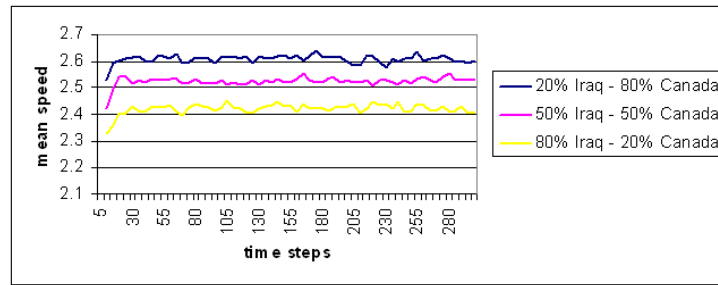

Figure 28: **Impact of mix population of Iraq and Canada on mean speed**

We also wanted to examine the impact of mix cultures on pedestrians' flow. The results are presented in graph 29. The results show that the highest flow has been found in population where 80% from Canada and only 20% from Iraq. The lowest flow has been found in population where 80% from Iraq and only 20% from Canada.

5.4 Experiment 4: Comparison to human data

The previous experiments focused on the use of simulation to investigate the effects of individual or bundled cultural parameters on overall crowd behavior. But an important underlying question is whether the fidelity of the simulation is sufficient to support conclusions as to human crowds.

Thus in this section, we examine whether the simulation can produce similar behavior to that of the observed human pedestrian crowd. We quantitatively compare the macro level measures (flow and mean speed) generated by the simulation to those of the crowds in the videos. We do not compare the number of collisions for this, as humans rarely collide—never in the video recordings—because they employ a more sophisticated obstacle avoidance algorithm than the simulation does.
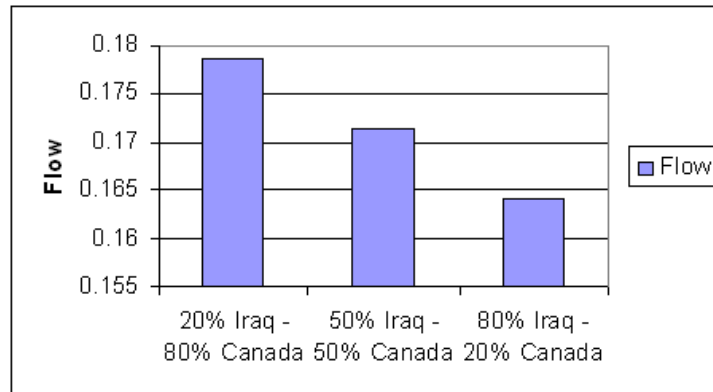
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Figure 29: **Impact of mix population of Iraq and Canada on pedestrians' flow**

To carry out the comparison, we recreated the initial settings in four of the videos in simulation. Specifically, we set the density of the pedestrian crowd (how many pedestrians per unit area); we set the individual parameters of agents and groups per the measured quantized values from the videos; and we ran the simulation for the same time as the videos. Note that we did not place simulated pedestrians in the initial locations of human pedestrians, as such fine-resolution placement should not affect macro-level crowd dynamics. Human subjects measured human crowd flow and mean speed by sampling pedestrians in the videos, and those sampled values were compared to the flow and mean speed analyzed direction from the simulated trajectory data.

5.4.1 Flow comparison

Flow defined as number of persons that cross a certain line divided by the width of this line and the time this process takes. To extract the flow from the human pedestrians movies, we need to define the sizes of the sidewalk or of the examined area. To estimate the exact sizes from the movies may become to a big challenge, and the main reason for this is the position of the camera. However, there are several movies that have a very good conditions to provide a sufficiently good approximation of these sizes. Thus, we analyzed the flow from 4 different movies, two from France (1:40 min and 2:47 min each), one from Canada (3:36 min) and one from London (30 sec), and the analysis was done only the portions of the videos in which the deducible part is visible. It has been shown that density has a big impact on the flow [25] and to quantitatively compare the simulation flow to the human pedestrian flow we need to account for the density. To extract the density from the examined human pedestrian movies, we sample the number of pedestrians in defined area every 5 seconds, and used the average number over all the samples.

Table 13 presents the densities of the examined movies. The first column presents the examined video, then we presents the height and the width of the sidewalk, the resulting squared area, the average number of pedestrians it included, and the density.

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The density is measured according to the following equation: *area*/*#people*.

Movie	Height	Width	Area	#People	Density
France1	25m	5m	125m2	8.238	15.17
France2	16.5m	5.5m	90.75m2	5.5	16.5
Canada	9m	3.9m	35.1m2	4.428	7.92
London	12m	12m	144m2	7.4	19.4

Table 13: **Human pedestrians movies: Density analysis**

The flow values were manually extracted from the four analyzed videos of the human pedestrians, in the following manner: For each video, we count the number of pedestrians passing a certain line (determined to be the "finish" line, i.e., one of the height borders of the sidewalk). The time variable is assigned with the number of seconds measured and the width of the sidewalk defined in Table 13. The flow calculated as following: number of agents that cross a certain line divided by the width of this line and the time this process takes.

To quantitative compare the extracted flow from the human pedestrians movies to the simulation flow, we need to create an accurate approximation of the human pedestrians analyzed scene. First we need to convert the values from human pedestrian analysis into simulation values. We used the ratio between person width in human pedestrians (which is approximately 0.5 m), and the agent width in the simulation (which is 1). For example, in Canada movie the size of the measured sidewalk is 9X3.9 meters, in our simulation it will converted to the 18×7.8 based on the conversion rate.

Figure 30 presents the results. The x-axis corresponds to the examined movie and the y-axis corresponds to the flow measurement. For each movie, we presents two bars, the blue bar corresponds to the flow that were extracted from human movie and the white bar corresponds to the flow that received from our simulation. The results show that in France1 we get 15% error, in France2 we get 4% error, the maximal error that we received is 16% which is in Canada movie and in London we received 10% error. The mean error that we received is 11%. Note that because the simulation is using low-resolution discrete results (e.g., only three values for speed) and mean values overall, a perfect match is essentially impossible.

5.4.2 Speed comparison

In this experiment we want to quantitatively compare the mean speed of human pedestrians to the our agent's mean speed in the examined movies. The human pedestrian mean speed is the mean speed values calculated from the videos analysis. The simulation mean speed is the mean speed value calculated from the simulation.

Figure 31 presents the results. The x-axis corresponds to the examined movie and the y-axis corresponds to the mean measurement. For each movie, we presents two bars, the blue bar corresponds to the mean speed that were extracted from human movie and the white bar corresponds to the mean speed that received from our simulation. The results show that in France1 we get 21% error which is a maximal error, in France2 we
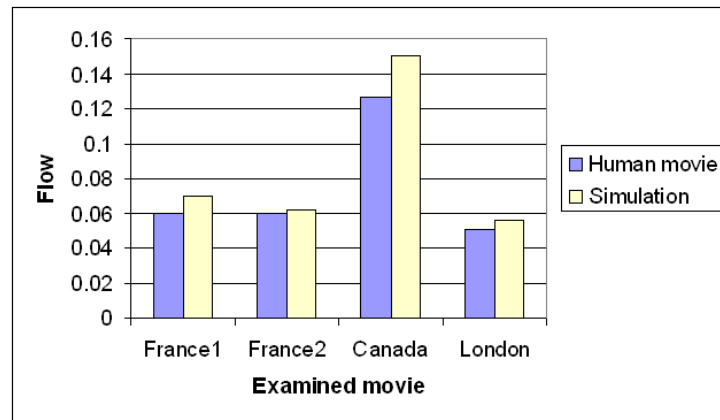
Figure 30: **Flow comparison to human data**

get 16% error, in Canada we received 10% error and in London we received 6% error. The mean error that we received is 13%.
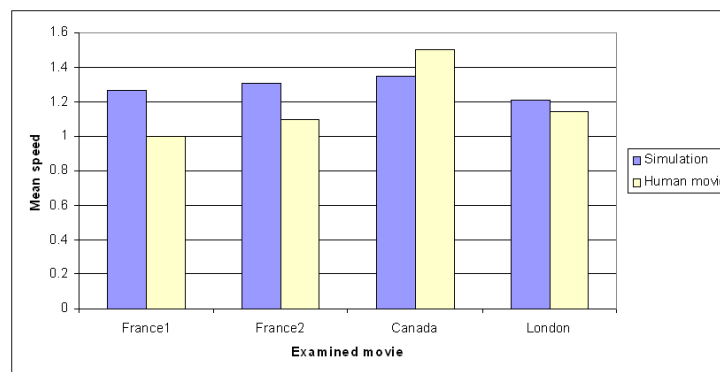

Figure 31: **Mean speed comparison to human data**

6 Cultural Differences in Evacuation Domain

Cultural differences also have been found in evacuation domain. For example, Swedish participants evacuated more in groups than Australians that evacuated more individually. It has been documented that some cultures take the event in different levels of seriousness and also in different level of fear. Moreover, it was found that in some cultures there is more tendency to notifying others about the event in comparison to other cultures. Finally, cultural differences also found to influence the manner in which peo-

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ple evacuate themselves, as there are cultures who tend to evacuate more in groups, while others prefer to evacuate individually more often. Based on literature we extract the cultural difference factors during the evacuation scenarios such as seriousness, notifying others and group behavior. In this section we define each of these factors in details and by using evacuation simulation we examine the impact of these factors on the resulting macro level behavior, such as evacuation time, average speed, etc.

During the evacuation, people tendency of notifying others regarding the event has been found as cultural. It has been documented that different cultures tend to notify others about the existence of the event, to different extents. For example, in U.S there is a higher tendency of notifying others regarding the event than in England [7].

The level of seriousness, regarding the participants association with the fire alarm and also their feelings during the event, has also been found to be another cultural attribute. It has been found that there is a significant difference between the Australian and Swedish populations when it comes to the emotions of fear and insecurity. People in Australia associated the alarm to a greater extent with something serious and they also felt a higher level of fear and insecurity than the Swedish participants [1]

Another cultural differences also found to influence the manner in which people evacuate themselves while there are some cultures that prefer to individually while other prefer to evacuate in groups. For example, it has been found that Swedish participants seemed to evacuate in groups more often than Australians which more often evacuated individually [1].

7   The Impact of Cultural Differences on Evacuation: Evaluation

To model evacuation behavior, we used ESCAPES which is a multiagent evacuation simulation [27] that incorporates four key features: (i) different agent types; (ii) emotional interactions; (iii) informational interactions; (iv) behavioral interactions among agents. ESCAPES was used to model evacuation behavior in the International Terminal at Los Angeles International Airport (LAX). It has been shown that ESCAPES provides a good results for modeling evacuation behavior. Moreover, it received a high praise from LAX security officials.

To examine cultural differences in evacuation behavior, we used the same scenario as described in [27]. This is a simulation of the airport with 4 terminals and 4 available exits where individuals agents and also families are all wandering freely around in shops or in available areas before the event. After the event, agents evacuate themselves. Moreover, in this simulation there is also a presence of the authority figures which before the event their task is to patrol and after the event their task is to inform other agents about the event and about the available exits. Each agent has a subset of 14 available behavior which it selects one, using a common architecture based in a BDI framework, based on its knowledge about the world and about other agents. For more realistic simulation, agents have an incomplete knowledge about their environment in particular about the available exits and also about the event. Each agent hold an event certainty value (integer between 0 and 2) which indicated on agent's awareness

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regarding the event and when event certainty is high an agent will decide to evacuate. Each agent has also a specific levels of emotions which affect its behavior during the evacuation, in particular on its speed. Speed is modeled as an integer value between 0 and 3, and fear is modeled as an integer value between 0 and 2 (FearFactor) where 0 indicating that the agent has no fear. Higher levels of fear lead to higher movement speeds. Moreover, agent's fear is affected from several factors such as its proximity to the event (increase agent's event certainty and also increase agent's fear), presence of authority figures (decrease agent's fear) and more. Agents that decide to evacuate also spread the knowledge about the event to their neighbors.

Cultural differences have been found in the tendency of people to notify others regarding the event, in their level of seriousness regarding the event and also in the way people tend to evacuate themselves. To examine the impact of these cultural differences on the resulting macro level behavior we used the following measures:

- Evacuation time: in each cycle we will save the amount of agents that are still in the terminal.

- Fear: Number of agents with HIGH fear versus LOW fear.

- Connectivity: number of connectivity components in the adjacency matrix of the agents

- Speed: the mean speed of the agents

7.1   Experiment 1: The impact of notifying others on evacuation

The tendency of notifying others regarding the event has been found as cultural attribute, while in some cultures people have more tendency of notifying others than in others cultures. In this section we want to examine the impact in the tendency that agents have to notifying others regarding the event, on the produced macro level behavior. In ESCAPES simulation, agents that are close to the event location have a full knowledge regarding the event, however agents that are far from the event are unaware about what happen. Agents that aware of the event will pass their event certainty to other close to them agents.

In this experiment we vary the percent of the close neighbors to whom an agent pass its knowledge regarding the event and examine the impact on the evacuation time and on agent's fear factor. Moreover, since in our simulation authority figures also notify others regarding the event, we examine the impact of notifying others with and without authority figures.

First we wanted to examine the impact of agents' knowledge passing on the evacuation time and also on their fear level, with no presence of the authority figures in the simulated environment. Figure 32 presents the results of the agents' evacuation time. The x-axis represents the time steps and the y-axis represents the % of unevacuated agents. The results clearly show that the more agents communicate the faster the evacuation time. However, there was no significant difference between agents that pass the event knowledge to all close neighbors (100% message passing) and agents that pass the knowledge to 80% of close neighbors (80% message passing), according

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to two-tailed t-test, $alpha = 0.26$. However, there is a significant difference between 80% of message passing and 50% of message passing (two-tailed t-test, $alpha = 0.04$). Moreover, there is a significant difference between 50% of message passing and 20% of message passing (two-tailed t-test, $alpha < 0.01$). Significant difference also examines between agents that pass the knowledge to 20% of close neighbors and agents that pass no knowledge at all (two-tailed t-test, $alpha < 0.01$).
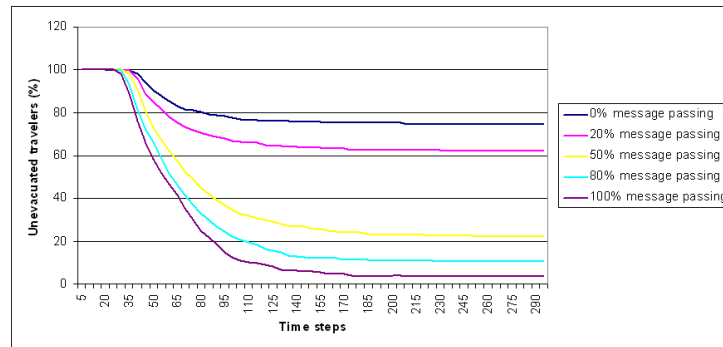
Figure 32: **The impact of agents' knowledge passing on the evacuation time (without authorities)**

We also wanted to examine the impact agents' knowledge passing on their fear level. Figure 33 presents the results. The x-axis represents the time steps and the y-axis represents the amount of unevacuated agents with FearFactor = 2. The results show that the more agent notify others regarding the event the higher will be the fear level in the population.
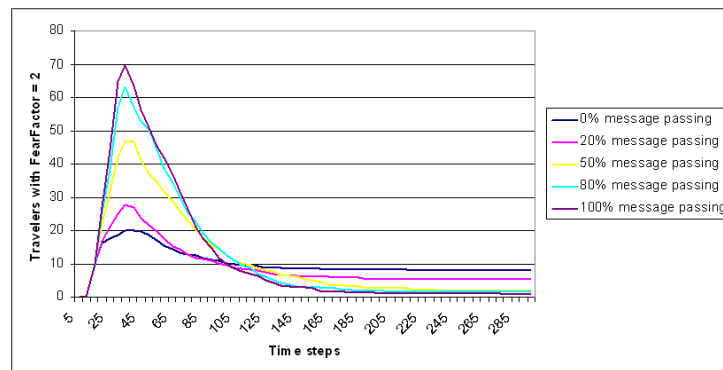

Figure 33: **The impact of agents' knowledge passing on the fear factor (without authorities)**

Now we wanted to examine the impact of the agents' knowledge passing on the

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evacuation behavior with the presence of 5 authority figures in the simulation environment. First we wanted to examine the impact of agents' knowledge passing on the evacuation time. Figure 34 presents the results. The x-axis represents the time steps and the y-axis represents the % of unevacuated agents. The results show that the more agents notify others regarding the event the faster will be the evacuation time. However, the authority figures cause almost no effect in evacuation time among fully communicable agents (100% notify others) in comparison to Figure 32. For example, the mean evacuation time in population with 5 authority figures and among 100% fully communicable agents is 24.5 while the mean value among same fully communicable agents but in population without authorities (Figure 32) is 23.4, which is not significantly lower (according to one tailed t-test, $alpha = 0.42$). However, among not communicable agents (0% notify others), the authority figures has a big impact. For example, the mean evacuation time in population with 5 authority figures and among not communicable agents (0% notify others) is 45.05 while the mean value among same not communicable agents but in population without authorities (Figure 32) is 80.2, which found to be significantly lower (according to one tailed t-test, $alpha < 0.01$).
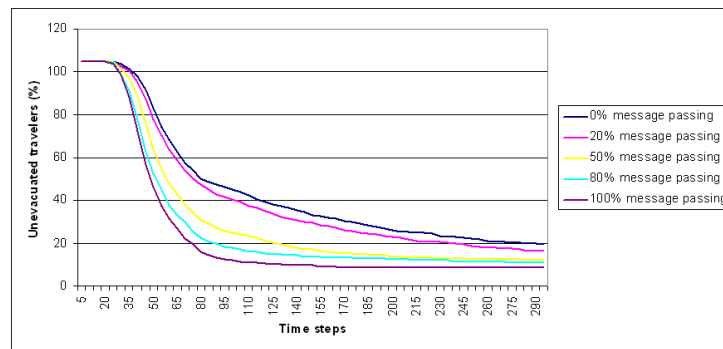

Figure 34: **The impact of agents' knowledge passing on the evacuation time (with authorities)**

We also wanted to examine the impact of agents' knowledge passing on the fear factor. Here again we examine the population with the presence of 5 authorities figures. Figure 35 presents the results. The x-axis represents the time steps and the y-axis represents the amount of unevacuated agents with FearFactor = 2. The results show that more communicable agents have higher fear. Moreover, the authority figures cause to lower fear among agents in comparison to population without authority figures (Figure 33). For example the mean value of amount of agents with FearFactor = 2 in population where 100% fully communicable agents and with 5 authority figures is 5.2 while the mean value of 100% of fully communicable agents without authority figures is 12.2, which is significantly higher (one tailed, t-test $alpha < 0.01$). Another example: the mean value in population of not communicable agents (0% notify others) and with authority figures is 3.3 while in same population of agents but with authority figures the mean value of amount of agents with FearFactor = 2 is 10.09, while again it is

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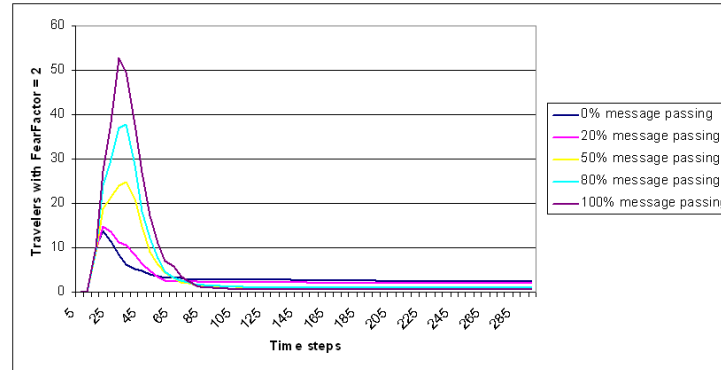found to be significantly higher (one tailed, t-test *alpha* < 0.01).

Figure 35: **The impact of agents' knowledge passing on the fear factor (with authorities)**

7.2 Experiment 2: The impact of seriousness level on the evacuation

The level of seriousness, regarding the participants association with the fire alarm has been found to be another cultural attribute. This level of seriousness affect participants' level of fear during the event. In this experiment we wanted to examine the impact of agent seriousness as the influence on its fear, on the produced macro level evacuation behavior.

In our simulation each agent holds an eventCertainty variable which indicates on the knowledge that agent has regarding the event and also a fearFactor variable that defines agent's level of fear. In ESCAPES simulation the eventCertainty variable has a direct influence on the agent's fearFactor thus if an agent has a HIGH eventCertainty then its fearFactor is also going to be HIGH. To account for the cultural difference in different level of seriousness that people have during the evacuation, we modify our simulation as following: we define different level of seriousness that agent can have (not serious, semi serious, very serious). Now, when an agent knows about the event (eventCertainty = HIGH) the agent's fearFactor going to affected based on agent's seriousness level: serious agents would get really afraid (fearFactor = HIGH), semi serious would get slightly less afraid (fearFactor = LOW), and others not be affected at all (fearFactor = NONE).

In this experiment we vary the percent of serious agents versus semi serious agents and examine the impact on the evacuation time, agent's fear factor and their mean speed (since agent's speed affected by its fearFactor – the more agent afraid the faster it will run to the exit). In our simulation an authority figures has a calming effect, they notify others regarding the event but they also reduces the fear level of the agents thus, we examine the impact of seriousness with and without authority figures.

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First we wanted to examine the impact of agents' seriousness on the evacuation time, mean speed and also on their fear level, with no presence of the authority figures in the simulated environment. Figure 36 presents the results of the agents' evacuation time. The x-axis represents the time steps and the y-axis represents the % of unevacuated agents. The results show that there is a faster evacuation time among more serious agents. There is also found a significant difference between population of all serious agents (100% seriousness) and population of no serious agents (0% seriousness), according to two-tailed t-test with $alpha = 0.004$.
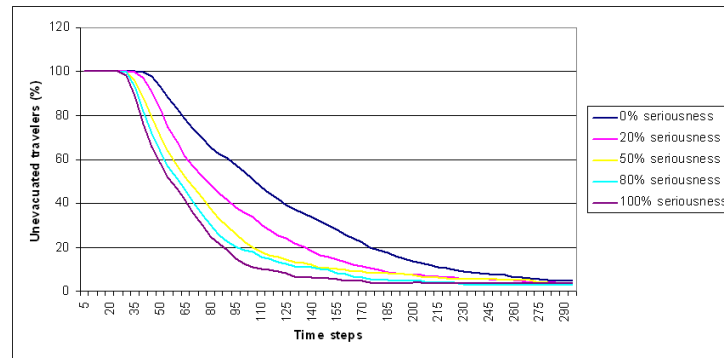

Figure 36: **The impact of agents' seriousness on the evacuation time (without authorities)**

The same pattern was also observed in evacuators speed. Figure 37 presents the results of the impact of agents' seriousness on the evacuators mean speed. The results show that more serious agents have faster speed. There is also found a significant difference between population of 20% serious agents (20% seriousness) and population of no serious agents (0% seriousness), according to two-tailed t-test with $alpha < 0.01$.
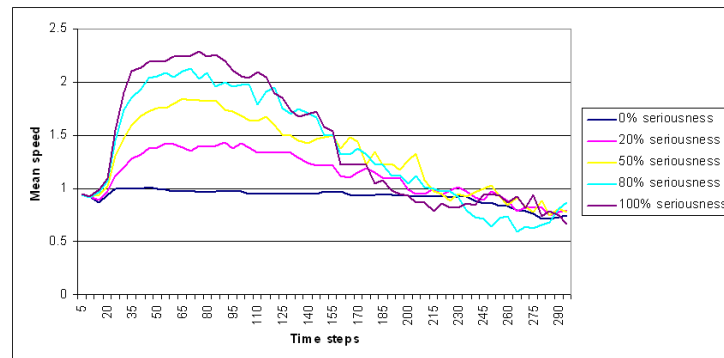

Figure 37: **The impact of agents' seriousness on the mean speed (without authorities)**

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We also wanted to examine the impact of agents' seriousness on their fear level, with no presence of the authority figures in the simulated environment. Figure 38 presents the results. The x-axis represents the time steps and the y-axis represents the amount of unevacuated agents with FearFactor = 2. The results show that higher seriousness cause to higher fear.
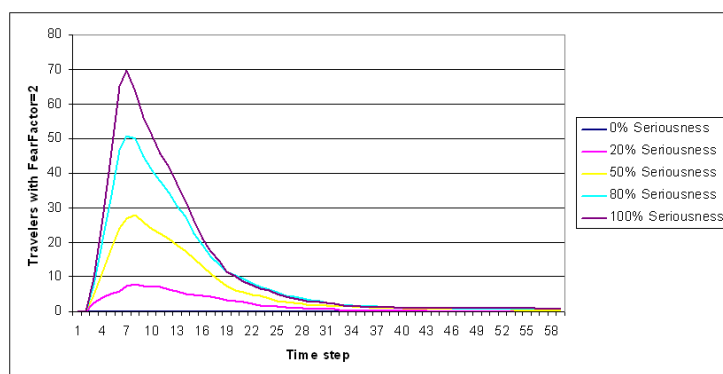

Figure 38: **The impact of agents' seriousness on the fear factor (without authorities)**

Now we wanted to examine the impact of the agents' seriousness on the evacuation behavior with the presence of 5 authority figures in the simulation environment. First we wanted to examine the impact of agents' seriousness on the evacuation time. Figure 36 presents the results. The x-axis represents the time steps and the y-axis represents the % of unevacuated agents. The results show that authorities figures cause almost to no change in the evacuation time between serious and less serious agents. Moreover, there is no significant difference between population of all serious agents (100% seriousness) and population of no serious agents (0% seriousness), according to two-tailed t-test with $alpha$ = 0.39. Moreover, the authority figures cause almost no effect in evacuation time among serious agents (100% seriousness) in comparison to Figure 36. For example, the mean evacuation time in population with 5 authority figures and among 100% serious agents is 24.5 while the mean value among same serious agents but in population without authorities (Figure 36) is 23.4, which found to be not significantly lower (according to one tailed t-test, $alpha$ = 0.42). However, among no serious agents (0% seriousness), the authority figures has a big impact. For example, the mean evacuation time in population with 5 authority figures and among no serious agents (0% seriousness) is 29.6 while the mean value among same not serious agents but in population without authorities (Figure 36) is 41.1, which found to be significantly lower (according to one tailed t-test, $alpha$ = 0.03).

We also wanted to examine the impact of agents' seriousness on the evacuators mean speed. The results are displayed in Figure 40. The results show that authority figures cause to agents' be much less time with high speed (speed level > 2) in comparison to graph 37. The results also show that authority figures have almost no impact on population with 100% of seriousness, for example: the mean speed of 100% serious
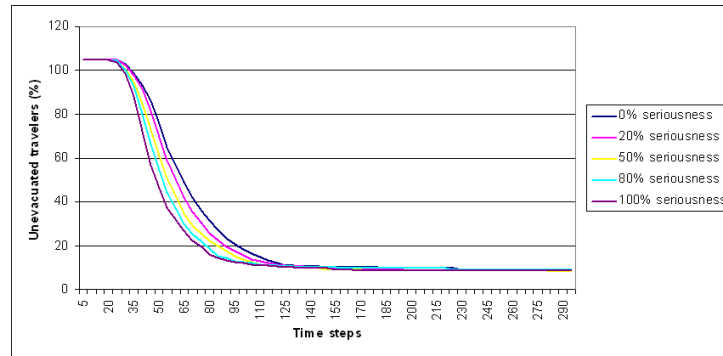
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Figure 39: **The impact of agents' seriousness on the evacuation time (with authorities)**

agents with 5 authority figures is 1.43 while the mean speed of 100% serious agents without authority figures is 1.42. The main reason for this is that on the one hand the authority figures have a calming effect which cause agents to reduce their speed but on the other hand they notify other agents regarding the event which cause them to increase their speed. However, in population of not serious agents (0% seriousness) authority figures have an impact, for example: the mean speed of 0% serious agents with 5 authority figures is 1.3 while the mean speed of 0% serious agents without authority figures is 0.9, which found to be significantly lower (according to one tailed t-test, $alpha < 0.01$).
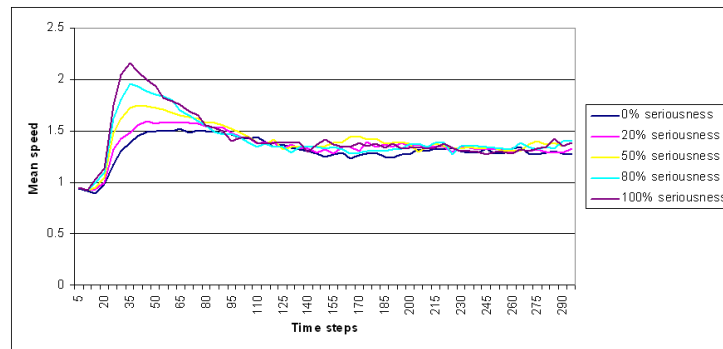

Figure 40: **The impact of agents' seriousness on the mean speed (with authorities)**

Now we wanted to examine the impact of agents' seriousness on the fear factor. Here again we examine the population with the presence of 5 authorities figures. Figure 41 presents the results. The x-axis represents the time steps and the y-axis represents the amount of unevacuated agents with FearFactor = 2. The results show that more serious agents have higher fear. However, the authority figures cause to lower fear

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among agents in comparison to population without authority figures (Figure 38). For example the mean value of amount of agents with FearFactor = 2 in population where 100% serious agents and with 5 authority figures is 5.2 while the mean value of 100% serious agents without authority figures is 12.2.
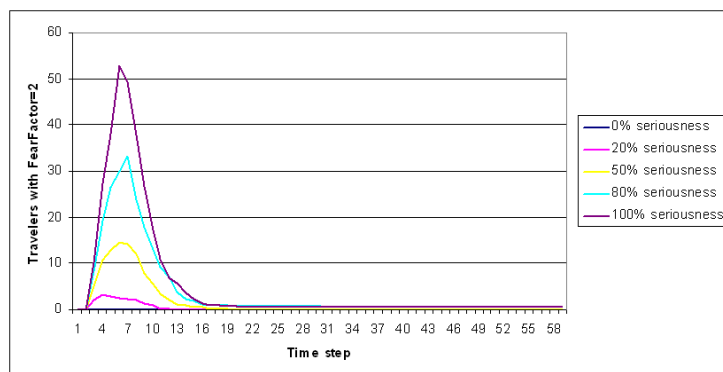

Figure 41: **The impact of agents' seriousness on the fear factor (with authorities)**

7.3 Experiment 3: The impact of group behavior on evacuation

In our final experiment we wanted to examine the tendency that people have in the way they evacuate themselves on the produced evacuation behavior. It has been shown that some culture evacuate in groups while others evacuate more as individuals.

In ESCAPES simulation has been shown that the use of SCT increases grouping behavior. The SCT computational model can be used, for instance, by agents who wish to exit an area, urgently. If they do not know the location of a close exit, they may turn to mimicking others hoping that they will lead them to safety. The use of SCT in evacuation leads to increasing grouping of the agents, as it will be shown in the experiments results. While in our previous work we show the impact of the SCT on the agents' density (connectivity), here we will also show the impact of the SCT on the evacuation time, their fear factor and on agents' mean speed. Moreover, we will also examine the impact of the authority figures on the produced behavior while we experiments with the populations with and without authority figures.

First we examine the population without authority figures. To examine the impact of agents' grouping behavior on the evacuation we compare between agent with SCT process and agents without SCT process and measure agents' evacuation time, connectivity, fear factor and mean speed. Figure 42 presents the impact of SCT on the agents' connectivity. The results show that agents' with SCT process have much higher connectivity which indicate on more grouping behavior than agents without SCT process. Moreover, the connectivity of agents' with SCT has been found to be significantly higher than agents without SCT, according to one tailed t-test, $alpha = 0.01$.

We also wanted to examine the impact of the SCT process on the agents' evacuation time, their fear factor and mean speed. Here again we examine the population without
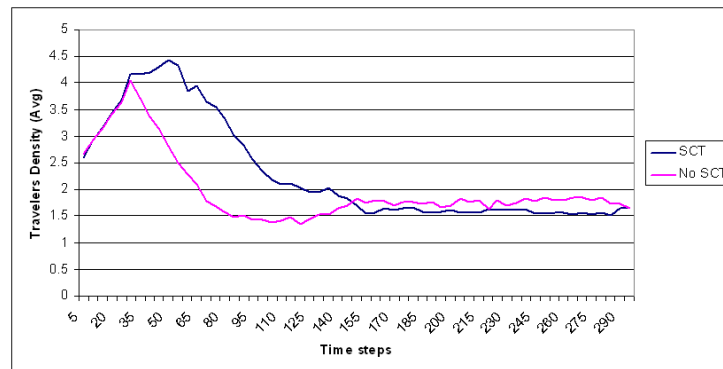
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Figure 42: **The effect of SCT on density (without authorities)**

authority figures. Figure 43 presents the results of the evacuation time. The x-axis represents the time steps and the y-axis represents the % of unevacuated agents. The results show that while the evacuation with the SCT seems to be a slightly bigger than without SCT, it found to be not significantly bigger, according to one tailed t-test, $alpha$ = 0.3.
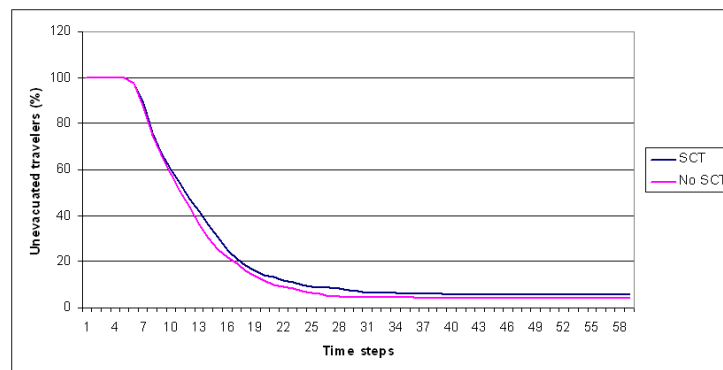

Figure 43: **The effect of SCT on evacuation time (without authorities)**

Figure 44 presents the results of agents' fear factor. The x-axis represents the time steps and the y-axis represents the number of agents with FearFactor = 2. The results show that there is no significant difference in fear factor between agents with SCT process and without SCT process, according to two tailed t-test, $alpha$ = 0.9. Finally, we also wanted to examine the impact of the SCT process on the agents' mean speed.

Figure 45 presents the results of agents' mean speed. The x-axis represents the time steps and the y-axis represents the mean speed. As in previous results there is no significant difference in mean speed between agents with SCT process and without SCT process, according to two tailed t-test, $alpha$ = 0.9.
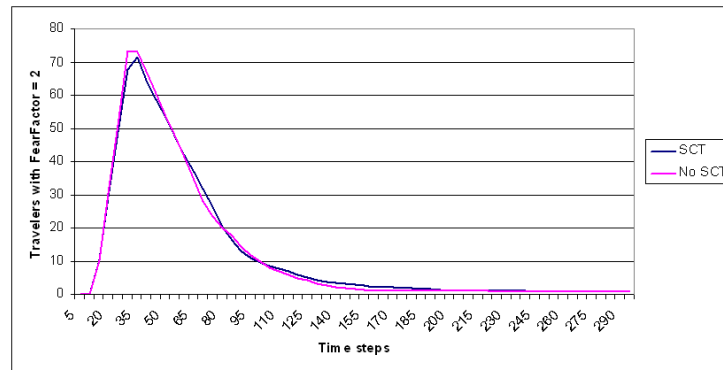
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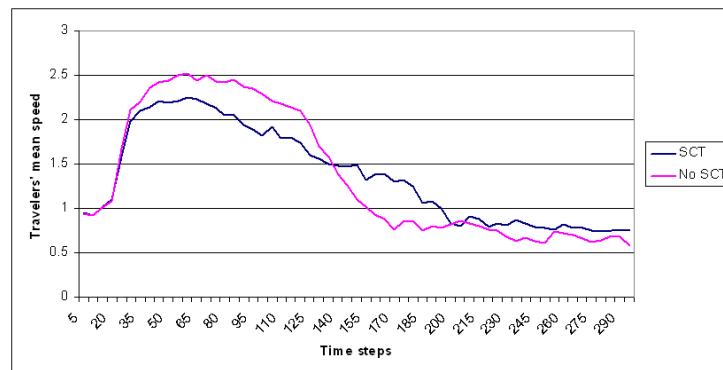Figure 44: **The effect of SCT on fear factor (without authorities)**

Figure 45: **The effect of SCT on mean speed (without authorities)**

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Now we wanted to examine the impact of SCT process on the population with authority figures. We define 5 authority figures and as in previous experiments we measure the agents' evacuation time, their fear factor, connectivity and mean speed. Figure 46 presents the impact of the SCT process on agents' density. The x-axis corresponds to the time steps and the y-axis corresponds to the agents' connectivity. As opposed to the population without authority figures, here there is no significant difference in connectivity between agents with SCT process and without, according to two-tailed t-test, $alpha = 0.49$.
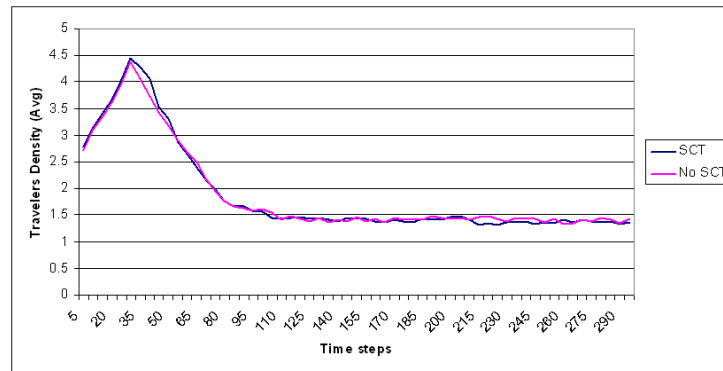

Figure 46: **The effect of SCT on density (with 5 authorities)**

Similar results were also received on agents' evacuation time, fear and mean speed. Figure 47 shows the results of the evacuation time. As in previous graphs, the x-axis represents the time steps. The y-axis represents the number of unevacuated agents. The results show that there is no significant difference in evacuation time between agents with SCT process and without, according to two tailed t-test, $alpha = 0.48$. The results regarding the agents' fear factor are presented in Figure 48. The results also show that there is no significant difference in agents' fear factor between agents with SCT process and without, according to two tailed t-test, $alpha = 0.88$. We also wanted to examine whether there is a difference in agents' mean speed between agents with SCT process and without. Figure 49 presents the results. Here again the results show no significant difference in agents' mean speed between agents with SCT process and without, according to two tailed t-test $alpha = 0.65$.

8   Summary

In this report, we took first steps to explore the impact of micro-level, individual agent, cultural parameters on macro-level crowd behavior. Building on existing literature which investigates culture in human crowds, we identified important cultural parameters in two physical crowd domains (pedestrian movement and evacuation). We implemented these in established agent-based simulations for these domains, and used the simulations to measure their impact on crowd dynamics. We thus go beyond ex-
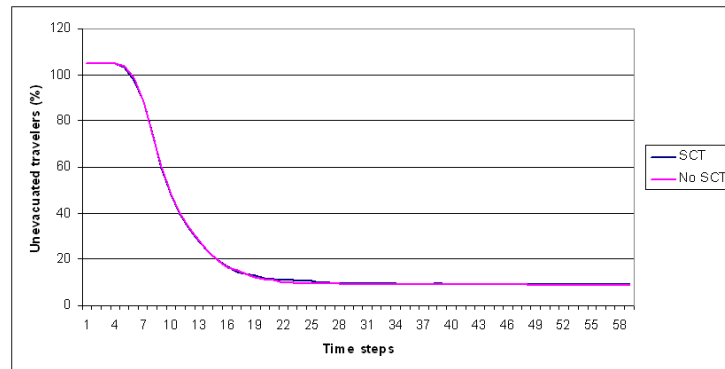
56

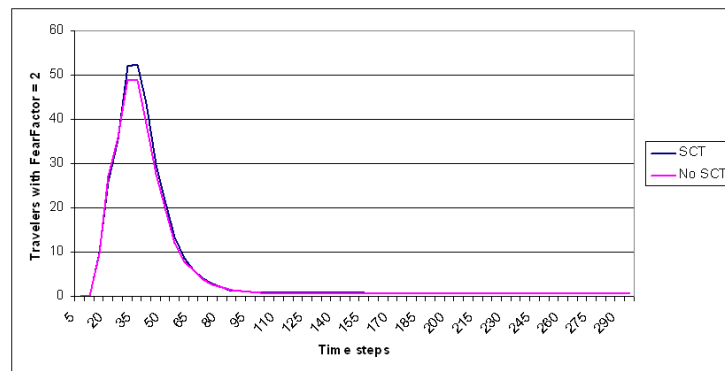Figure 47: **The effect of SCT on evacuation time (with 5 authorities)**

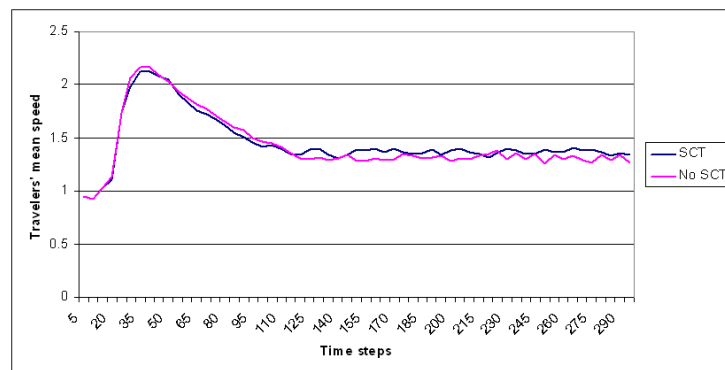Figure 48: **The effect of SCT on fear factor (with 5 authorities)**

Figure 49: **The effect of SCT on mean speed (with 5 authorities)**

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isting work, which focused on describing cultural parameters of individuals, without investigating their crowd-level effects.

In the pedestrian motion domain, we conducted three sets of experiments. The first explored first the effect of each parameter by itself, in mixed crowd settings (mixed, in the sense that the parameter in question was varied among the agents). The second explored mixing agents, each with a pre-set bundle of such parameters (i.e., a present values for each of the parameters, that match recorded videos from different countries and cultures. Finally, the results of the simulation were quantitatively validated against data extracted from videos of crowds in five different countries.

In the evacuation domain, we presented a subset of results which demonstrate how cultural parameters (such as the seriousness with which evacuees treat indications of the need to evacuate) affect evacuation time and panic levels. For these, we additionally examined the effect that authority figures can have on the evacuation measures. We found that in some cultures (in particular where agents treated evacuations seriously), guards did not speed up evacuations. In others (in particular where agents did not take evacuations seriously), guards had a calming effect (lowering panic), while still increasing the rate of evacuation.

We believe that there are two important directions for future work on this research. The first involves continuing our work on collecting and analyzing movies of crowds in different culture. We believe that it would be possible, given the right funding, to form an international collaborations with colleagues in different countries, to collect data and make it available to crowd researchers world-wide. We believe that the availability of annotated, analyzed data is a real stumbling block in this field.

The second direction of research which we hope to pursue takes advantage of the high accuracy predictions made by the models we have developed. Building on their fidelity, it should now be possible to start investigating their use for tasks other than simulation. For instance: How can we use these models to identify suspicious behaviors (e.g., a person posing as a pedestrian, but really not belonging to the crowd)?

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